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Design of Congestion Prediction Model on Network Towers using Rough Set Theory for High Speed Low Latency Communication

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Abstract: Wireless communication for data and a variety of wireless interacted devices have increased dramatically in the past few years. Millimeter wave (mmWave) technology can serve the primary objectives of 5G networks, which include high data throughput and low latency. But mmWave signals for communications lacking substantial diffraction and are consequently more susceptible to obstruction by environmental physical objects, which could cause communication lines to be disrupted and congestion takes place. Wireless data transmission suffers from blockages and path loss, causes high latency as well as reduces the data transmission speed and degrades in quality performance. To overcome the limitations, Rough Set Theory with hypertuned SVM is implemented and designed the congestion prediction model based on the behaviour of network towers for low latency and high-speed data transmission. The data from the different towers is initially collected and created as a dataset. Super MICE is a technique to replace the missing data. Then, the Rough Set Theory is utilized to cluster the data into equivalent classes based on the behaviour of 5G, 4G and 3G wireless network. Hypertuned SVM with a Gazelle optimization algorithm is applied to predict the congestion level by accurately selecting the hyperparameter. By employing performance metrics, the proposed approach is examined and contrasted with existing techniques. The evaluation of performance measurements for the proposed method includes informedness attained as 91%, Adjusted Rand Index obtained value as 0.83, Jaccard as 0.737. Accuracy, precision, sensitivity, error, F1_score, and NPV are also achieved at 93%, 92%, 94%, 7%, 92%, and 90%, respectively. According to this evaluation, the proposed model is superior to perform than the earlier used existing methods.

Index Terms: Super MICE, RST, Hypertuned SVM, GOA, Congestion Prediction.

1. Introduction

Modern data networks largely depend on the Transmission Control Protocol (TCP) to maintain reliable connections [1]. Most Internet applications employ the transport layer protocol known as TCP, which controls the speed of transmission by effectively adapting the congestion window (cwnd), and that specifies the highest possible amount of data a sender is permitted to send on the basis of the congestion control algorithms (CC) used to control congestion in the network [2]. Furthermore, reliable packet delivery is assured in the event of packet loss via retransmitting as well as retrieving the lost packets in accordance with the acknowledgement (ACK) message sent by the receiver. Numerous TCP congestion control investigations have been carried out to enhance throughput and minimize latency in response to the rapid growth of network technology and popularity in wireless Communication [3]. Owing to the desired performance of 5G networks, the best networks using 5G must enable Gigabits per second (Gbit/s) and their user bitrate must offer a minimum of 50 megabits per second (Mbit/s) [4]. To meet the throughput requirements for potential 5G networks, high-bandwidth millimeter (mmWave) communications may be crucial. More advanced end-to-end throughput may be expected for mmWave bands that allow frequencies of 24 GHz and above since they offer an additional usable bandwidth than current mobile communication networks [5]. Despite the fact that the mmWave band is thought to be an attractive technology for satisfying the objectives of 5G wireless networks in multi-gigabit per second transmission rates with very low latency, the entire network's performance realized by clients will ultimately be defined based on how it communicates in the transport layer protocol.

In today's world, the increased use of wireless networks includes WLAN and Wi-Fi leads to higher traffic on the internet [6]. The performance of the network in its entirety and the standard of communication suffers if traditional TCP is used on this network's connections that may be diverse in nature. One of the fundamental elements in the TCP protocol constitutes the TCP CC. Through the use of various algorithms, it has seen a great deal of advancement over time [7]. The early TCP specification failed to consider network congestion and only evaluated flow control as a way to avoid the receiver end's buffer from overflowing. Numerous CC protocols were originally developed for overcoming network congestion in particular criteria regards to latency, bandwidth, and packet loss rate. Traditional congestion control techniques like TCP Reno [8], TCP Tahoe [9] and TCP New Reno [10] establish unwanted losses in the Congestion Window (CWND) that severely reduce its performance of TCP wireless senders/receivers. The CWND is aggressively increased by some algorithms, as TCP BIC [11], to compensate the losses, whereas it fails to ensure intra and inter fairness. TCP Cubic was created to address this issue by enhancing TCP's scalability under significant BDP situations while maintaining fairness. Wi-Fi networks have serious bandwidth variations because of their severe loss rate. Although TCP Westwood and TCP Veno were designed to solve circumstances with bandwidth variation, they failed to perform as well as TCP CUBIC [12]. Google, therefore invented TCP BBR [13], and that adapts to variation bandwidth and minimizes losses in heavy BDP conditions. Researchers have emphasized that difficulties and significant signal fluctuation across mm-wave networks lead to inefficient resource use, which lowers TCP throughput.

Recent research investigations have found that the mmWave channel's substantial and frequent signal variations, which lower end-to-end throughput, prevent the available bandwidth from being entirely exploited. Maintaining the TCP cwnd value that corresponds to the ideal channel state is required for properly utilizing the mmWave link's available bandwidth, however regular deterioration of the wireless channel's quality affects the link's usable bandwidth [14]. Despite the fact that the link's capacity decreases as caused by bad radio waves channel quality, the sender of TCP is unable to instantly decrease the cwnd and sends a lot of packets. As a result, the number of packets transmitted exceeds the wireless link's capacity, which builds up in the base station's buffer and creates a long queue. Network users recognize poor service due to the lengthy queuing delay created by the buffer bloat problem, which additionally extends the round-trip time (RTT). To overcome the drawbacks, a Wireless Tower Behaviour based congestion prediction model has been designed in this model. Contributions of the proposed method are as follows:

- Design of congestion prediction model using rough set theory with hyper tuned SVM based on the behaviour of different network towers for high speed and low latency communication.
- Data are collected from network towers and formed as a dataset for clustering the tower into different classes based on their behaviour using the rough set theory.
- Super multiple imputation by chained equations (MICE) imputation replaces each missing value for handling missing data in the entire dataset.
- Rough set theory is used to divide the dataset into similar data subsets and analyze the behaviour of these subsets or equivalence classes based on their tower behaviours.
- Hyper tuned SVM based on the Gazelle optimization algorithm (GOA) is used for learning the parameter to predict the congestion level.

The next sections are laid out as different works that have been analyzed and deal with congestion control in TCP wireless networks are described in section 2, and section 3 describes the proposed methodology. In Section 4, the experimental outcomes for the proposed framework are provided, and the final section in Section 5 gives a summary of the entire research tasks.

2. Literature Review

Many CCs have been created in recent years to address the issue of network congestion as well as to improve TCP's overall performance in particularly networks. The most extensively used transport layer protocol is TCP, which offers dependable end-to-end communication due to its connection-oriented design. Different TCP variations exist, each with unique qualities that make them suitable in particular circumstances.

Yang et al. [15] developed a Loss-Aware Throughput Estimation scheduler (LATE), a new scheduler for multipath TCP in diverse wireless connections that combines a loss-based transmission scheme and packet segment scheduling strategy. In order to accurately predict the amount of data that may be delivered over every sub flow in a provided time as well as decide which segments need to be assigned to specific sub flows, LATE attentively takes into consideration every sub flow's route property and protocol parameters such as congestion window (cwnd), Round Trip Time (RTT), and loss rate. According to research results, LATE increases mean throughput along with long-lasting flows by 5.13% while decreasing the overall completion period for quick flows at roughly 26.68%.

Saedi and El-Ocla [16] presented a TCP variant as CERL Plus (CERL+) for enhancing the wireless networks performance. TCP Reno was modified at the sender-side in TCP Congestion Control Enhancement for Random Loss

(CERL+). Though it functions similarly to TCP CERL, TCP CERL+ was a new generation whose core concept was to apply a dynamic threshold with regard to RTT. In order to do this, it required measurements of the connection's average and minimum RTT to determine the bottleneck link's queue length. Therefore, analyzed the congestion condition and separated this from random loss status using this queue length. In turn, this would prevent the window size from shrinking, improving the efficiency of the developed technique by enhancing the data transmission rate. Additionally, it was apparent that CERL+ reduces congestion in the bottleneck.

Li et al. [1] introduced an improved scheme of TCP proxy acknowledgement based on Automatic Repeat Request (ARQ). It was better suited to emerging asymmetric networks and increases throughput, decreases delay, and conserves uplink bandwidth in wireless connections. During the experiment, a significant improvement in protocol efficiency for processing was seen. According to the observed data, the total time required to process every packet was almost equivalent to one-fourth of the transmission control protocol, and the usage of resources has decreased by 59%. In order to increase throughput under busy wireless environments, the protocol includes a number of straightforward approaches for loss recovery. The findings demonstrate that the use of mean diversity combining technologies can increase throughput and performance of effective factors while lowering the need for radio link protocol (RLP) maximal retransmission durations. The uplink bandwidth consumption rate was greatly increased since almost 90% of uplink ack packets were filtered. To enhance system performance, large data frames might be divided into smaller data frames.

Olmedo et al. [17] demonstrated a wireless TCP protocol improvement, examining a negative acknowledgement (NACK), allows for a distinction from losses caused by wireless channel problems and losses by congestion. TCP-NACK protocol, which adds an error notification named "NACK" to the capabilities of the Generic TCP protocol, suffers from issues with wireless performance. The alert informs the broadcaster that corrupted packets have arrived and instructs them to immediately retransmit without the reduction of CWND. The quality of service measurements are improved by NACK, which uses a short protocol packet. The tests were conducted in real-time scenarios using indoor and outdoor settings, a video game scenario played online, and a long-distance wireless network connecting two islands. When compared to the original TCP Reno protocol, the mean outcomes demonstrate a 25% improvement in delay and a 5% improvement in jitter.

Na et al. [18] depicted a DL-TCP appropriate in the disaster mmWave 5G range. If the packet loss incidence happens, the deep learning model forecasts the connection separation time by learning the link separation timing depending on the signal strength and node mobility data. By properly controlling the cwnd size in accordance with the projected time, as proved by NS-3-based simulation, without wasting mmWave bandwidth DL-TCP was designed. This cannot be a radical way to eliminate link error because the model that was generated refers to the loss-based TCP model whereby a lost packet incident occurs. To minimize obstructions in the mmWave band and to offer an uninterrupted communication environment by beam management technique, the deep-learning design described in the research can also be applied to the beam reflection technique.

Poorzare and Augé [19] presented a new Fuzzy logic-based TCP that aims to avoid a reduction in the performance of urban deployments. The new protocol's congestion avoidance stage employs fuzzy rules to dynamically alter the data transfer rate and mitigate the effects of blockages. The protocol's ultimate goal is to regulate the transmission rate on the basis of the state of the network in order to get the best performance. Additionally, aimed to prevent buffer fatigue, it strives for low latency and minimizes the average transmitting rate. In-depth simulations shown that, in the urban environment, the newly created protocol could perform better than High Speed, BBR, New Reno and Cubic in terms of throughput, RTT, and sending rate adjustment.

Alrshah et al. [20] established a new delay-based and RTT independent congestion control algorithm (CC), namely Elastic TCP. The creative window-correlated weighting function (WWF) was the key contribution, which helps networks with high bandwidth-delay products (BDPs) networks used more TCP bandwidth. The performance of the introduced Elastic-TCP has been assessed through significant simulation as well as test bed studies by comparing it to the widely used TCPs established by Linux, Microsoft and Google. The findings demonstrated that the presented Elastic-TCP maintains loss ratio and sharing fairness while averaging a greater throughput compared to the other TCPs. It's also important to keep in mind that the new Elastic-TCP is more stable and efficient than other TCPs because it was less sensitive to packet error rate and changes in buffer size.

Joseph Auxilius Jude et al. [21] introduced a FAIR+ algorithm that reduced the data transmission rate depending on the utilization status of TCP flows and begins the congestion control method focused on the relay node's queue level notification. The FAIR+ method used an updated window increment scheme during the congestion recovery phase, which have a higher convergence rate compared to the standard RFC 6582 implementation currently in use. With the help of the multi-hop wireless and duality model simulation, the throughput stability of the FAIR+ algorithm was confirmed. According to the simulation results, the FAIR+ significantly outperformed the other TCP variations such as OQS, Westwood and NRT in terms of flow fairness, throughput and end-to-end latency.

Some of the drawbacks obtained in reviewed articles are high resource consumption [15], if a random loss is observed, does not reduce the congestion window and slow start threshold [16], network exhibiting a high error rate may result in an excessive number of packets or frames of information being transmitted [1], requests for incomplete or false information [17], dependence on data quality [18], Exact rules and function of membership are difficult to achieve [19] and not utilizing the entire bandwidth of connection while waiting [20] and limited capacity [21]. However, the proposed model overcomes the above issues by Wireless Tower Behaviour based congestion prediction using rough set theory with hyper tuned SVM.

3. Proposed Methodology

A spectrum lacking issue has arisen due to increased traffic in several domains. While a millimetre wave (mmWave) band with enormous bandwidth that ranges from 30 to 300 GHz will serve as an essential aspect of the 5G technology Wireless network, the current technology can't always be able to satisfy forthcoming enormous demands. Many complications are added to improve communications, such building penetration loss human, and building obstructions with various dimensions, while the mmWave technology delivers a significant amount of 5G bandwidth assistance with booming applications. Figure 1 illustrates a process flow of the proposed model.

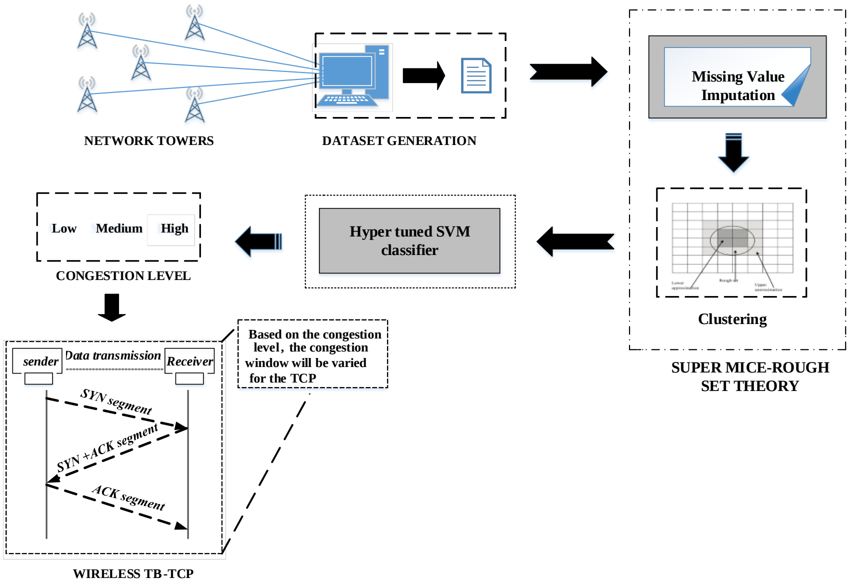

Fig.1. Process flow of the proposed model

In this designed model, a wireless Tower Behaviour based congestion prediction model has been designed. At first, the data from the various towers are collected and generated as a dataset. The missing data are replaced by super MICE imputation and their tower behaviours are clustered into different classes using the rough set theory, which is a technique used for the establishment of equivalence classes within the given training data. Then, the hypertuned SVM classifier learns the parameter to determine the congestion level as low, medium and high with the Gazelle optimization algorithm (GOA) to optimally select the parameter and based on the level of congestion, the congestion window is varied automatically in the wireless Tower.

3.1. *Super MICE Imputation*

Missing data is a common issue in all practical real-world datasets [22]. It is defined as instances of variables with incomplete information. Generally, the issue with missing values is that the outcomes formed by a dataset with missing values can be less accurate and the analyses can't be done correctly based on the data. The super MICE imputation approach refers to a semi-parametric method for estimating missing data employing super learner and MICE [23]. It produces values for data that is missing using a normal distribution and mean calculated using a Super Learner model with a local estimate of the variance during the process.

Consider a set of data with the form$Z = (z_1, z_2, \dots, z_r)$ that consists of N binary and numerical vectors where any of the variables may have missing values. It doesn't matter how the variables are ordered. Furthermore, establish a $N \times r$ binary matrix, $\delta = \delta_{pq}$, where

$$\delta_n = \begin{cases} 0 & z_{pq} \text{ is missing} \\ 1 & z_{pq} \text{ is observed} \end{cases} \tag{1}$$

Additionally, a library of prediction algorithms (L) having cardinality f should also be considered. Employ the notation $0 \le s \le T$ to represent an algorithm iteration. Lastly, use the superscript *(u, s)* to identify the u^{th} sets of data in the s^{th} iteration of the method. Describe the phases of MICE utilizing Super Learner in the remaining paragraphs of this section.

Initialization: Generate h equivalent data sets from the tower as follows: $z^{(1,0)}, z^{(2,0)}, \dots, z^{(h,0)}$. Assign $z_{pq} = 0$ for every missing value,$\delta_{pq} = 0$, and thereafter compute the value for the associated variable, z_p, applying the mean (approximate to 0 or 1, when binary) of the values that are observed. In other words,

$$z_{mn}^{(h,0)} = \frac{\sum_{q=1}^{N} z_{pq}\delta_{pq}}{\sum_{q=1}^{N} \delta_{pq}} \tag{2}$$

Prediction: For variable $1 \leq q \leq r$ and for data set $1 \leq u \leq h$, so q has a minimum of one missing value, fit every method $l \in L$, anticipating $z_q^{(u,s)}$ from $Z_{(q)}^{(u,s)}$, the data or information with g eliminated. The weighted average of the estimates made by the collection of algorithms in the library provides the Super Learner (SL) predictions.

$$\hat{z}_q^{(u,s)} = \hat{\Psi}_{SL,q}^{(u,s)}\left(Z_{(q)}^{(u,s)}\right) = \sum_{l=1}^{g} \hat{\alpha}_{ql}^{(u,s)} \hat{\Psi}_{ql}^{(u,s)}\left(Z_{(q)}^{(u,s)}\right), \tag{3}$$

In the case where $\Psi(.)$ is a functional yielding predictions by the algorithm and the range of predicted weights, $\hat{\alpha}_q = (\hat{\alpha}_{q1}, \hat{\alpha}_{q2}, \ldots, \hat{\alpha}_{qg})$ so that $\sum_{l=1}^{g} \hat{\alpha}_{l.q} = 1$ are determined simply by reducing the cross-validated risk.

Imputation: Determine the missing data using a semi-parametric method. With probability matching the Super Learner forecasts, values are extracted based on a Bernoulli distribution in the binary instance. In the case of continuous variables, the values of missing data are chosen at random from a normal distribution, whose mean is determined by the Super Learner forecast and whose local estimation of variance. The local variance is calculated using weighted variance that gives observations as greater weight along with anticipated values that are equivalent to the value that is missing and observations in regions with a higher percentage of missing data.

In particular, the weights are calculated using the formula $w_{mn}(z) = \delta_{mn} w_{mn}(z)/\hat{\pi}(z)$, for a kernel function $K_b(.)$ and bandwidth b. where

$$w_{mn}(z) = \frac{K_b(z - \hat{z}_{mn}^{(u,s)})}{\sum_{p=1}^{N} K_b(z - \hat{z}_{mn}^{(u,s)}} \tag{4}$$

With the typical Nadaraya-Watson weights and $\hat{\pi}(z) = \frac{K_b(z - \hat{z}_{mn}^{(u,s)})\delta_{mn}}{\sum_{p=1}^{N} K_b(z - \hat{z}_{mn}^{(u,s)}}$ is a close-proximity estimation of missingness. A successful outcome depends on the bandwidth selection.

Following that, the weighted variance can be evaluated as

$$\hat{\sigma}_{mn}^{2(u,s)} = \frac{\sum_{p=1}^{N} w_{mn}(\hat{z}_{mn}^{(u,s)})(\hat{z}_{mn}^{(u,s)} - \hat{z}_{mn}^{*(u,s)})^2}{\sum_{p=1}^{N} w_{mn}(\hat{z}_{mn}^{(u,s)})} \tag{5}$$

Where weighted mean is denoted by$\hat{z}_{mn}^{*}$. $\hat{z}_{mn}^{*}$.

Lastly, a sample of each missing value from the relevant distribution is taken.

$$z_{mn}^{(u,s+1)} \sim N(\hat{z}_{mn}^{(u,s)}, \hat{\sigma}_{mn}^{2(u,s)}) \tag{6}$$

Repeat the prediction and imputation processes until T iterations (often 10–20 is enough).

Estimation: The standard MICE approach is used for pooling and estimation of the values and average error rates for every one of the j imputed data sets:

a) Every imputed data set is subjected to statistical analyses (such as regression) just as if the data were complete.

b) Rubin's rules are then used to integrate the analysis estimates. In other words, where I stand for the quantity of interest and$\left[\hat{I}^{(q)}, C^{(q)}\right], q = 1, \ldots, j,$ denotes the set of estimated parameters and standard errors for every imputed data set. The overall integrated parameter estimation can be calculated by the simplest average $\bar{I} = \frac{1}{j}\sum_{q=1}^{j} \hat{I}^q$ and the overall variance is described as

$$V = \bar{C} + A + A/j \tag{7}$$

Where between-imputation variance is determined as $A = \frac{1}{j-1}\sum_{q=1}^{j}\left[\hat{I}^q - \bar{I}\right]^2$and the within-imputation variance is given by $\bar{C} = \frac{1}{j}\sum_{q=1}^{j} C^q$.

3.2. Rough Set Theory

Rough Set Theory is based on the establishment of equivalence classes within the given training data of the tower behaviours [24]. The tuples that form the equivalence class are indiscernible. It means the samples are identical with respect to the behaviours of the tower describing the data. Based on this model, the collected datasets from the tower are classified as low, medium and high congestion according to the behaviour of the tower.

Rough set theory is a new soft computing method introduced by Z. Pawlak that is used for processing inconsistent, ambiguous, and uncertain data [25]. Attribute reduction, or the deletion of least informative qualities, is a crucial application of the RS theory. When equivalence relations between sets of tower behaviours are generated, a reduction in behaviours can be performed. When behaviours are removed using the dependence degree as a measurement, the smaller behaviours set delivers the same degree of dependency as the original set. The term "rough set" describes the topological operations, which are further referred to as approximations. Researchers from all over the world have recently been interested in this technology. It is an effective technique in the field of artificial intelligence and is applied as a hybrid technique in machine learning and data mining. Data tables are analyzed in rough set theory. Experts or sampling can obtain data tables according to this notion. A decision table containing rows of items and columns of criteria or behaviours can be used to represent typical data. In order to describe the basic set theory as an information system, use the 4-tuple technique as shown in Equation (8).

$$T = (U, V = G \cup H, R = \{R_c | c \in V\}, l = \{l_c | c \in V\}) \tag{8}$$

Where a finite incomplete set of tower behaviours is known as *c*, and *U* is the universe of converse having a finite number of entities. The subsets *G* and *H* are referred to as the condition set and decision set, respectively. R_c represents the potential values of the tower behaviours *c*, and R is the nonempty set of all possible values. Additionally, the information function is denoted as *l*, $l_c(y)$ indicates the value of entities $y \in U$ regarding the tower behaviours *c*. simply write $T = (U, V, R, l)$ to represent the information system.

Considering a subset of the tower behaviours $C \subseteq V$ and the indiscernible relation indicated by IND(C) and specified in Eq. (9) is the following in rough set theory:

$$IND(D) = \{((y,z)|(y,z) \epsilon U^2, \forall_{c \epsilon C}(l_c(y) = l_c(z))\} \tag{9}$$

IND(C) is obviously an equivalence relation that is transitive, symmetric, and reflexive. The family of all *IND(C)* equivalence classes will be written as $U|INB(C)$, or, or just $U|D$, and an *IND*(C) equivalence class containing *y* will be written as $[y]_{IND(C)}$, or just *[y]*. A diagram representation of rough set theory is illustrated in Figure 2.

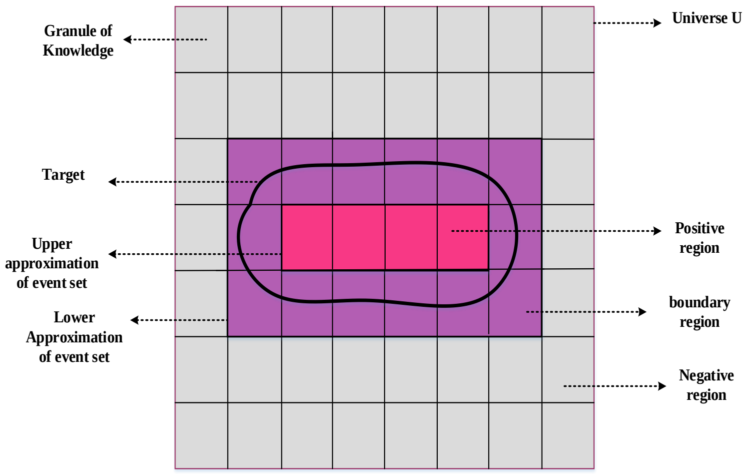

Fig.2. Diagram representation of rough set theory

The lower and higher approximations of Y with regard to the set of tower behaviours Care specified by taking into account the relationship between equivalence classes. Low approximation is defined as the range that can be reasonably assumed that belongs to the intended collection, and upper approximation is defined as the range that cannot reasonably be assumed to belong to the desired collection. The lower and upper approximations are provided in equations (10) and (11).

$$\underline{Apr}(Y) = \{y \epsilon U | [y] \subseteq Y \tag{10}$$

$$\overline{Apr}(y) = \{y \epsilon U | [y] \cap Y \neq\} \tag{11}$$

The boundary, positive, and negative regions of the universe *U*, which are described in Equations (12) to (14), can be divided into three separate parts.

$$BND_{area}(Y) = \overline{Apr}(y) - \underline{Apr}(Y) \tag{12}$$

$$Pos_{area}(Y) = \underline{Apr}(Y) \tag{13}$$

$$Neg_{area}(Y) = U - \overline{Apr}(y) \tag{14}$$

When an object has the property$y \in Pos_{area}(y)$, it definitely corresponds to the target set Y. While an object has the property$y \in BND_{area}(y)$, it may not necessarily be a member of the target set Y. It is impossible to determine whether an object y is a member of the target set Y if an object$y \in NEG_{area}(y)$.

3.3. Hyper Tuned SVM Classifier

Support Vector Machine (SVM) depends on statistical learning theory and was invented by Cortes and Vapnik [26]. SVMs are among the most popular machine learning (ML) approaches and are a class of algorithms for classification, regression, and other applications [27].

The basic SVM finds the ideal separation hyperplane from a set of training data: $\{p_j, q_j\}$, where $P_j \epsilon \mathbb{R}^d$ is the j^{th} input vector and $q_n \in \{+1, -1\}$ is the associated class label.

$$h(x) = v^T x + b \tag{15}$$

Where b refers to a scalar known as bias and v is a weight vector that is determined using a linear sum of considerably few data points termed support vectors. If data cannot be separated linearly, the subsequent quadratic modelling problem must be solved to determine the separating hyperplane using a set of slack variables, $\{\xi_j\}_{j=1}^{n}$,

$$\begin{aligned} &\min \quad \tfrac{1}{2} v^T v + S \textstyle\sum_{j=1}^{n} \xi_j \\ &\text{s..t. } q_j\left(v^T q_j + b\right) \geq 1 - \xi_j, \xi_j > 0 \; for \; j = 1, \dots, n \end{aligned} \tag{16}$$

Where S is a scalar parameter called the penalty factor. Introducing the nonnegative Lagrange multipliers λ and following the Karush-Kuhn-Tucker conditions, the problem in (16) becomes the following dual problem:

$$\begin{aligned} &\max L(\lambda) = \textstyle\sum_{j=1}^{n} \lambda_j - \tfrac{1}{2} \sum_{j=1}^{n} \sum_{j=1}^{n} p_j p_k \, \lambda_j \lambda_k K(q_j, q_k) \\ &s.t. S \geq \lambda_j \geq 0 \;\; \forall_j = 1, \dots, n, and \; \textstyle\sum_{j=1}^{n} \lambda_j \, p_j = 0 \end{aligned} \tag{17}$$

The function $K(q, q')$ in equation (16), specified on the$\mathbb{R}^d \times \mathbb{R}^d$, is said to be a kernel if it can be mapped to the Hilbert space $\varphi: \mathbb{R}^d \to H$ such that$K(q, q') = \langle \varphi(q), \varphi(q') \rangle$. This can be done by providing two random input vectors, q and q'. There are various methods for resolving the latest expression of the SVM issue, known as C-SVM. Under the assumption that a decision boundary with fewer support vectors will be less complex and therefore less prone to overfitting, the PSV (percentage of vectors$q_j$for associated$\lambda_j > 0, j = 1, \dots, n$) can be shown to be an accurate estimate of an SVM's generalization capability.

The Radial Basis Function (RBF or Gaussian) kernel, $K_{RBF}(q, q') = e^{-\gamma \|q - q'\|^2}$is one of the many possible forms that the kernel function can take. It has been extensively employed since the SVM theory's inception. The SVM formulation can have additional parameters added by the kernel function, such as the size of the basis function γ, which could have a substantial impact on how well this classifier performs. The following section introduces optimization methods that can be utilized to address the hyper-parameter tuning issue.

3.4. Gazelle Optimization Algorithm (GOA) for the Proposed Method

Gazelles have special qualities that help them successfully evade enemies [28]. According to studies, predators only successfully catch gazelles 34% of the time. This knowledge is used by the gazelle optimization algorithm (GOA) to create a novel metaheuristic algorithm that makes use of the survival skills of gazelles to address optimization issues in the real world [29]. The Sahara Desert, the sub-Saharan Sahel, and northeast Africa are just a few of the places where gazelles can be found and also live in portions of Asia and the Arabian Peninsula. For numerous predators, these creatures are viewed as one of the usual preys. Gazelles are agile, have sharp senses, and live in groups for social and security reasons, among other behavioural characteristics. These creatures are mostly plant-eating animals, and their social organization is such that the male's dwell in bachelor herds while the females inhabit smaller families of their calves. Predators including cheetahs, hyenas, jackals, lions and leopards hunt gazelles. Stotting, or leaping into the air, and running at incredible speeds are just two of the efficient defence mechanisms they have evolved over time.

The flow diagram of the proposed Gazelle optimization is depicted in Figure 3. Some of the steps that are examined for tuning the best parameter using Gazelle optimization are initiation, fitness function, update, and termination.

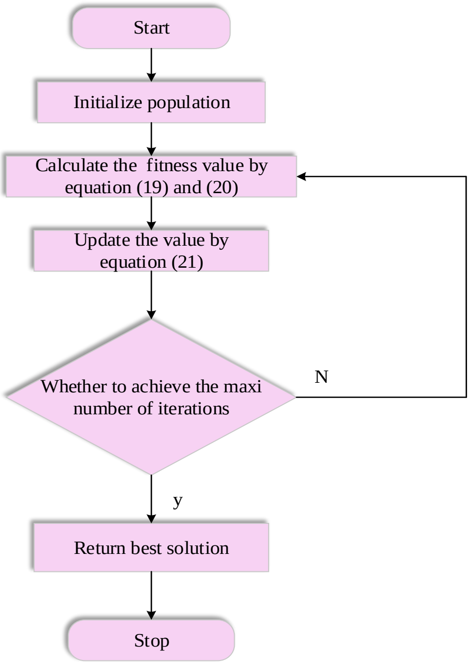

Fig.3. Flow diagram of the proposed gazelle optimization

Step 1: Initialization

The SVM algorithm tuning parameters kernel, regularization or C, gamma, and margin are utilized instead of populating the Gazelle optimization. These parameters are referred to as populationw_1, w_2, w_3, w_4.

$$\mathrm{F} = w_1, w_2, w_3, w_4 \tag{18}$$

Step 2: Fitness function

Optimizing the hyperprameter of SVM using the Monte Carlo method allows one to assess the fitness function for fine-tuning the classifier parameter.

$$fitness = \{\, maximize(acc) \tag{19}$$

$$mccv = \frac{1}{Mm_v} \sum_{k=0}^{M} \left\| V_{S_c(k)} - \hat{V}_{S_v(k)} \right\|^2 \tag{20}$$

A quick and efficient approach for dividing samples into two portions at random is Monte Carlo cross validation. For fitting the models, the first portion (calibration set), referred to S_c has m_c samples and for verifying the model, the second portion (validation set), referred toS_v, has samples with the formula$m_v = m - m_c$. After splitting the samples based on MCCV the prediction is done using simple KNN classifier and further the accuracy is calculated for each portion and the parameter value that attain maximum accuracy is selected.

Step 3: Updating

Following the initialization and fitness function processes, equation (21) is used to update every single other set of aspects. From the Gazelle optimization algorithm, the update equation is derived.

$$\overrightarrow{Gazelle_{j+1}} = \overrightarrow{Gazelle_j} + S.\mu.CF.R * \overrightarrow{R_b} * (\overrightarrow{elite_j} - \overrightarrow{R_l} * \overrightarrow{Gazelle_j}) \tag{21}$$

Where $CF = \left(1 - \frac{iter}{max-iter}\right)^{\left(2\frac{iter}{max-iter}\right)}$

Where $Gazelle_{j+1}$is the solution for the following iteration, $Gazelle_j$ is the solution for the current iteration, S is the pace at which the gazelles graze, R_b is a vector of constant random integers [0, 1], and R is a vector of different random numbers reflecting the Brownian motion. $R_l$is a vector of random numbers based on Lévy distributions. CF represents the cumulative effect of the predator.

Step 4: Termination

After the SVM parameter has been tuned to its optimal level. The entire optimization procedure will be terminated.

Algorithm: *Pseudocode for designing congestion prediction model on network towers using rough set theory with hyper tuned SVM*

Input: collect the data from different towers
TW=$T_1, T_2, T_3, \dots, T_n$
 # Missing value imputation
MI= super MICE (TW) // super MICE based missing value imputation is calculated by equation (1) to (7)
 # Clustering
R=RST (MI) // Utilized Rough set theory to determine clustering of equivalent classes by equation (8) to (14)
 # SVM with Gazelle Optimization
F = w_1, w_2, w_3, w_4 *// Define the parameter*
V = MCCV (F) // Fitness function is performed using equation (20)
D = GOA (V) // Optimally tune the hyperparameter by equation (21)
Hyper tuned =SVM (D) // SVM is performed by equation (15) to (17)
S = Hyper tuned (R) // Training and testing of the clustered data
 # Congestion level
If class (S=0)
Print (high)
Elif (S=1)
Print (medium)
Else
Print (low)
End

Output: *Determine the congestion level in wireless TCP*

4. Result and Discussion

Implementation and design of the proposed Wireless Tower Behaviour based congestion prediction model using Rough Set Theory and hyper tuned SVM is developed for high speed and low latency communication. The designed model is evaluated using the software Matlab R2021a, which has been set up on an Intel core i7 CPU, 64GB memory (RAM), and NVIDIA GeForce RTX 3070 GPU. Gathered data from the tower is created and the missing data is replaced by super MICE. Clustering into equivalent classes is done using rough set theory and hypertuned SVM with Gazelle optimization is optimally selects the hyperparameters for accurate classification of congestion level. At last, finite automata is designed for the proposed method.

4.1. Dataset Description

An enormous Irish mobile network provided a 5G trace dataset [30]. The dataset was produced using two modes of transportation (static and automobile) and two types of applications (video broadcasting and file download). The set of data consists of client-side wireless key performance indicators (KPIs) that include throughput data as well as metrics relating to channels, contexts, cells, and other factors. These statistics were produced by G-NetTrack Pro, a popular non-rooted Android network tracking tool. It is the first openly available dataset that includes efficiency, channel, and context data for 5G networks, in the highest standard of the data.

4.2. Confusion Metrics

Fig.4. Confusion metrics for the proposed method

Figure 4 demonstrates the confusion metrics of the proposed method. A confusion meter provides a table form for various results of the predicted outcomes and aids in the visualization of the results. This creates a table with all of a classifier's predicted and actual values.

Table 1. Based on confusion metrics for multi-class classification

	Predicted (1)	Predicted (2)	Predicted (3)
Actual (1)	TP= 331	FP= 0	FP= 19
Actual (2)	FP= 0	TP= 340	FP= 7
Actual (3)	FP= 23	FP= 2	TP=291

In Table 1, the multiclass classification's true positives and false positives are depicted. The given dataset's actual and predicted data are assessed using this confusion metric. The predicted data for classes 1, 2, and 3 are 331, 340, and 291, respectively. The total number of data used for testing is 1012, of which 961 are predicted correctly and the remaining 51 are incorrectly predicted.

Missing Value Imputation

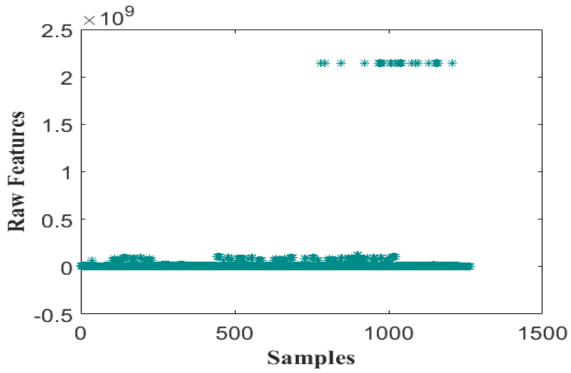

Fig.5. Raw features of the proposed method

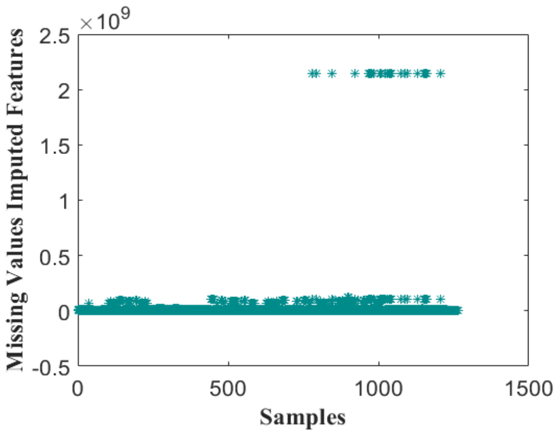

Fig.6. Missing value imputed features of the proposed method

Raw features and missing value imputed feature of the proposed method is described in Figure 5 and Figure 6, respectively. There were some missing values in the data set in some of its data input vectors and fills in those values with some correctly predicted ones for generating a complete dataset by using super MICE.

4.3. Performance Metrics for the Proposed Model

Performance measures for the designed model include Training, Testing, and Execution Times, as well as Precision, Accuracy, Specificity, sensitivity, Negative Predictive Value, Error, False Negative Value, False Positive Value, F1 Score, False Discovery Rate, Kappa, Mathew's Correlation Coefficient (MCC), False Omission Rate, Informedness, Adjusted Rand Index, Fowlkes-Mallows Index, bookmaker informedness, Normalized Mutual Information, Jaccard.

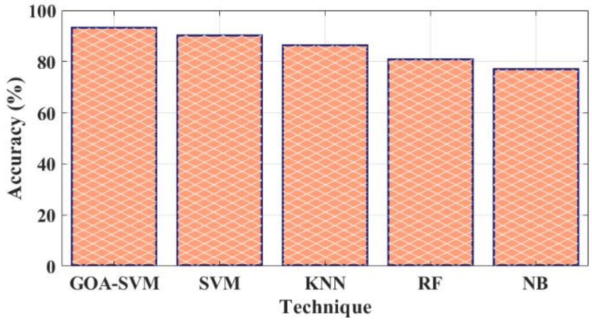

Fig.7. Accuracy comparison of proposed GOA-SVM with existing method

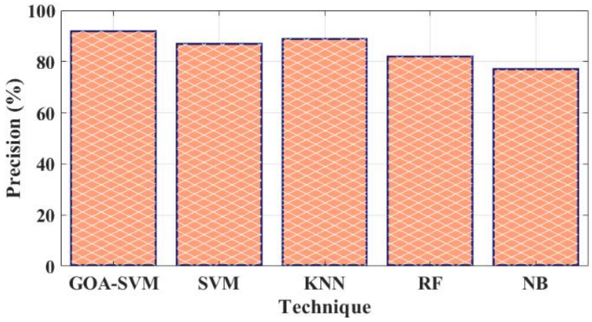

Fig.8. Precision comparison of proposed GOA-SVM with existing method

The accuracy assessment measures for both proposed GOA-SVM and existing approaches are described in Figure 7. The proposed GOA-SVM method is compared with the existing methods, including support vector machines (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), and Naive Bayes (NB), in this analysis. Accuracy is an indicator that assesses how often it predicts the outcome accurately. For GOA-SVM, SVM, KNN, RF, and NB, the accuracy values are 93, 90, 86, 81, and 77. The proposed GOA-SVM model has better accuracy for detecting the congestion level than the previously employed approaches. Figure 8 compares the precision measurements for the proposed GOA-SVM and the existing approach. Precision is a metric that assesses how frequently it predicts the positive class accurately. For GOA-SVM, SVM, KNN, RF, and NB, the obtained precision values are 92, 87, 89, 82, and 77. As a result, the GOA-SVM's precision value is higher than that of the existing model.

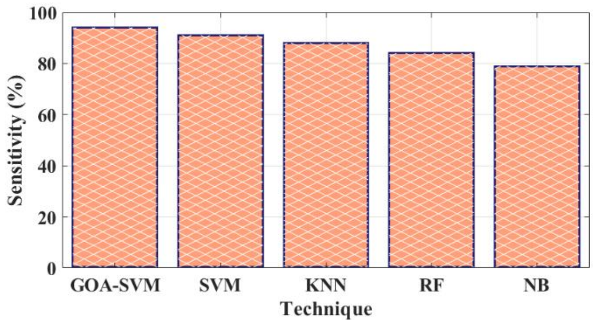

Fig.9. Sensitivity comparison of proposed GOA-SVM with existing method

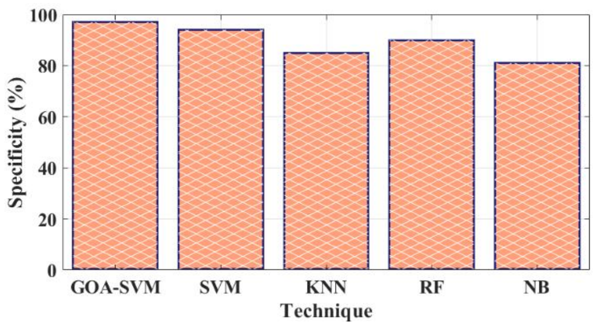

Fig.10. Specificity comparison of proposed GOA-SVM with existing method

Figure 9 illustrates the computation of sensitivity measures for both the proposed and existing models. Sensitivity can be utilized to assess the performance of models since it enables the number of occurrences that the model has the ability to accurately classify as positive. For GOA-SVM, SVM, KNN, RF, and NB, the determined sensitivity values are 94, 91, 88, 84, and 79. The GOA-SVM's sensitivity value is, therefore higher than that of the existing model as a result. The assessment of specificity measures for proposed and existing approaches are shown in Figure 10. The percentage of actual negatives that the model correctly predicts is known as specificity. For GOA-SVM, SVM, KNN, RF, and NB, the specificity values are 97, 94, 85, 90, and 81. In comparison to the current methods, the proposed GOA-SVM model has a higher specificity.

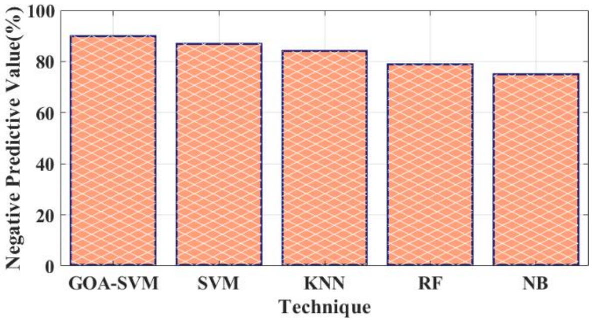

Fig.11. Negative Predictive Value (NPV) comparison of proposed GOA-SVM with existing method

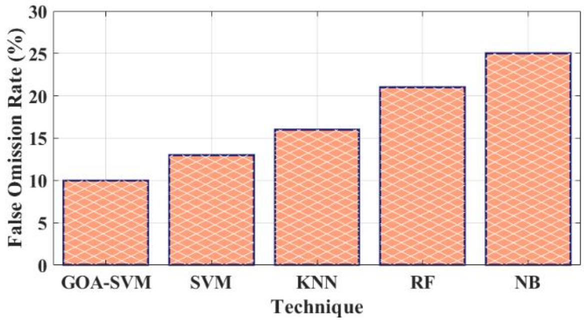

Fig.12. False Omission Rate (FOR) comparison of proposed GOA-SVM with existing method

Figure 11 illustrates the comparison of Negative Predictive Value (NPV) metrics for the proposed GOA-SVM and the existing model. The proposed and existing models, such as GOA-SVM, SVM, KNN, RF, and NB have achieved NPV values of 90, 87, 84, 79, and 75, respectively. Therefore, the proposed strategy GOA-SVM has a higher NPV value than the currently existing methods. The False Omission Rate (FOR) evaluation metric for both proposed and existing methods are shown in Figure 12. Attained FOR values for GOA-SVM, SVM, KNN, RF, and NB are 10, 13, 16, 21 and 25, respectively. The FOR values of the proposed GOA-SVM model are less than those of existing approaches.

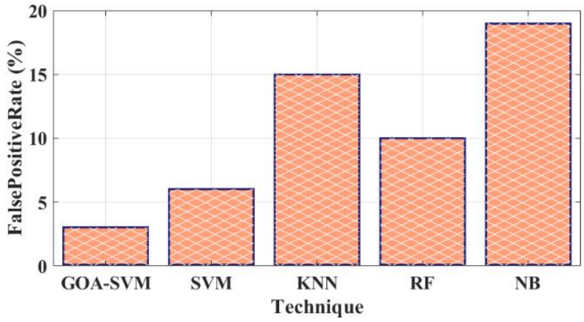

Fig.13. False Positive Rate (FPR) comparison of proposed GOA-SVM with existing method

Figure 13 shows the estimation of the False Positive Rate (FPR) for the proposed GOA-SVM and existing models. The outcomes for the proposed GOA-SVM technique and the already-in-use methods are SVM, KNN, RF, and NB models are 3, 6, 15, 10, and 19, respectively. In accordance with the false Negative Rate (FNR), Figure 14 compares the proposed GOA-SVM and existing techniques. For comparison, the false negative rate values for the proposed ROA-XGB and existing approaches are 6, 9, 12, 16, and 21. The acquired FPR and FNR values indicate that the proposed approach outperforms existing methods.

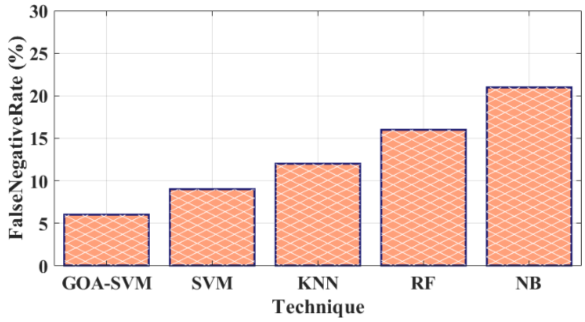

Fig.14. False Negative Rate (FNR) comparison of proposed GOA-SVM with existing method

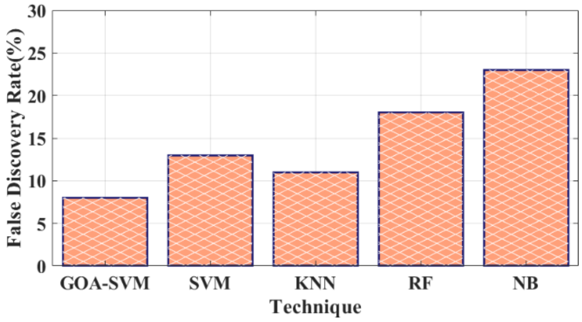

Fig.15. False Discovery Rate (FDR) comparison of proposed GOA-SVM with existing method

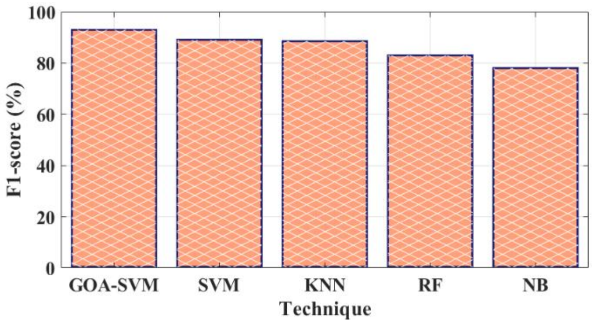

Fig.16. F1_score comparison of proposed GOA-SVM with the existing method

The False Discovery Rate (FDR) for both the proposed GOA-SVM and existing used techniques such as SVM, KNN, RF, and NB algorithms are examined in Figure 15. The FDR value of the proposed method is 8, compared to existing machine learning, such as SVM, KNN, RF, and NB values that are 13, 11, 18, and 23, respectively. The false recovery rate achieved from the proposed strategies is lower than the rate acquired using existing techniques. Figure 16 shows the F1_score evaluation for the proposed and existing models. For GOA-SVM, SVM, KNN, RF, and NB, the results obtained F1_score values are 92, 88, 88, 82, and 77. As a result, the GOA-SVM has a higher F1 score value than the existing techniques.

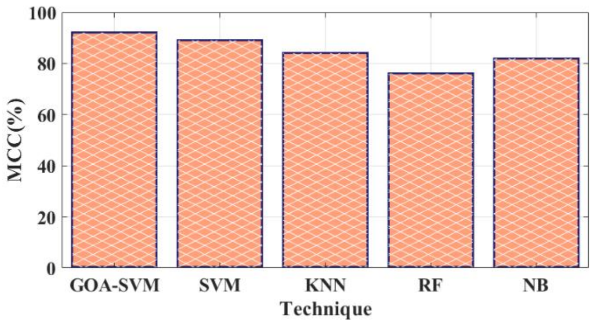

Fig.17. Mathew's Correlation Coefficient (MCC) comparison of the proposed GOA-SVM with the existing method

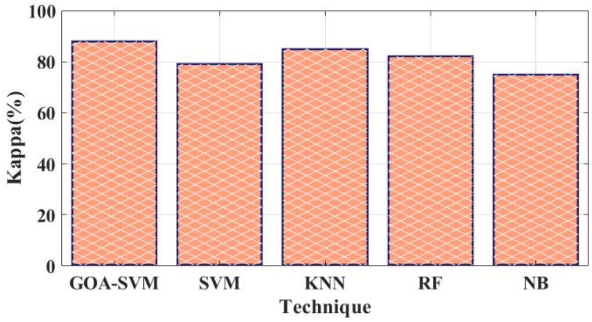

Fig.18. Kappa comparison of proposed GOA-SVM with existing method

Figure 17 compares the MCC performance of the proposed GOA-SVM to that of the existing approaches involving SVM, KNN, RF, and NB. The prediction only yields a high score if it performed well in each of the four regions of the confusion measurements (true positives, false negatives, true negatives, and false positives) proportionally based on the size of positive elements and negative elements in the dataset. The MCC values for GOA-SVM, SVM, KNN, RF, and NB are 92, 89, 84, 76, and 82, respectively. The MCC rating of the suggested procedure is thus greater than that of existing approaches. Figure 18 shows how the proposed technique and the existing approach fared in terms of the kappa metrics. The resulting kappa values for the proposed GOA-SVM and traditional approaches, such as SVM, KNN, RF, and NB, are 88, 79, 85, 82, and 75. Therefore, the proposed model's kappa values are higher compared to the values of each of the earlier used techniques.

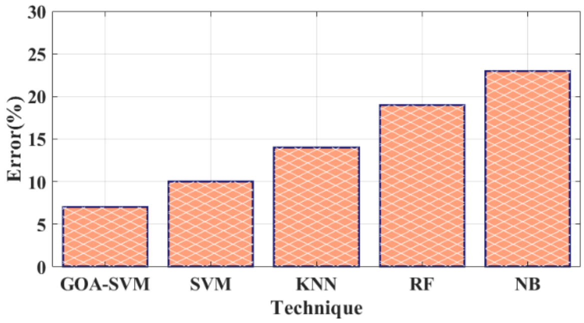

Fig.19. Error comparison of proposed GOA-SVM with existing method

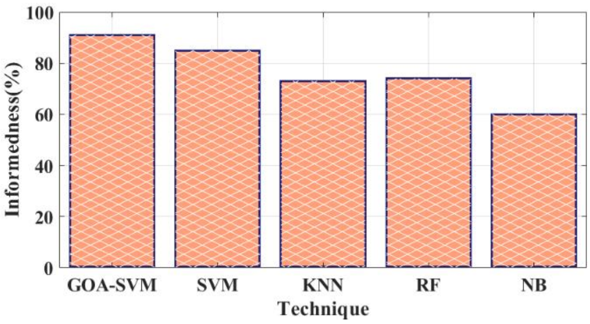

Fig.20. Informedness comparison of proposed GOA-SVM with existing method

In Figure 19, a comparison of the proposed GOA-SVM and existing methods based on error is presented. The proposed GOA-SVM approach and the already used SVM, KNN, RF, and NB algorithms both yielded error values of 7, 10, 14, 19 and 23, respectively. As a result, the proposed GOA-SVM approach has a lower probability of error than the existing model. Comparison of informedness for both the proposed GOA-SVM and existing methods, includes SVM, KNN, RF, and NB are depicted in Figure 20. It evaluates the likelihood that a decision will be made with sufficient knowledge and is generalized to the multiclass situation as informedness. The informedness outcome values for proposed GOA-SVM and existing techniques SVM, KNN, RF, and NB are 91, 85, 73, 74 and 60, respectively. Thus, the proposed method is superior compared to other existing techniques.

Evaluation of the Adjusted Rand Index both the proposed and existing techniques are illustrated in Figure 21. The values obtained for the proposed RST and existing methods includes FCM (Fuzzy c-means), KNN, and Agglomerative are 0.836, 0.764, 0.526 and 0.352. Figure 22 demonstrates the Fowlkes-Mallows Index comparison of the proposed RST with the existing method. The observed values are 0.956, 0.715, 0.648, and 0.527 for the proposed RST (Rough Set Theory) and existing methods like FCM, KNN, and Agglomerative. The figure shows the proposed RST perform well when compared to existing techniques.

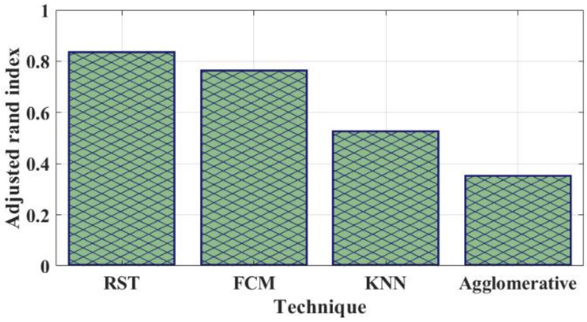

Fig.21. Adjusted rand Index comparison of proposed RST with the existing method

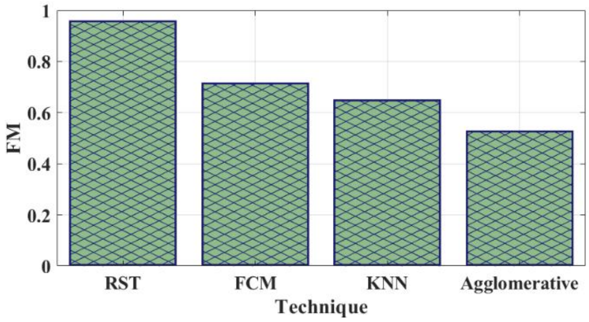

Fig.22. Fowlkes-Mallows Index comparison of proposed RST with the existing method

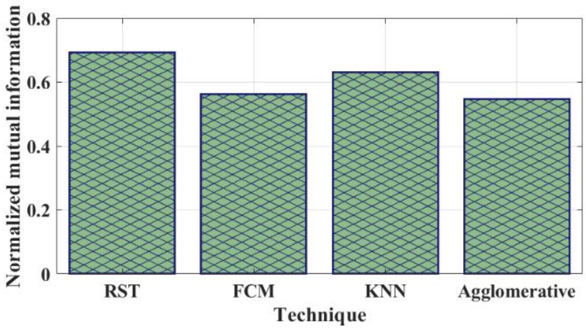

Fig.23.Normalized Mutual Information comparison of proposed RST with the existing method

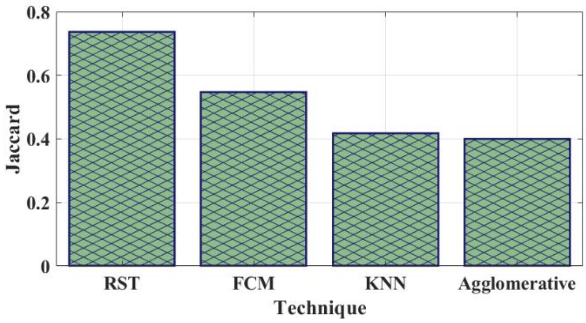

Fig.24. Jaccard comparison of proposed RST with the existing method

Figure 23 presents the examination of Normalized Mutual Information (NMI) for the proposed as well as existing techniques. The scores achieved are 0.692, 0.563, 0.632, and 0.546 for the proposed RST (Rough Set Theory) and existing methods like FCM, KNN, and Agglomerative. The Jaccard comparison of the proposed RST and the existing technique is represented in Figure 24. For the proposed RST (Rough Set Theory) and existing approaches like FCM, KNN, and Agglomerative, the discovered values are 0.737, 0.548, 0.417, and 0.401. The figure demonstrates that the proposed RST is superior to earlier methods.

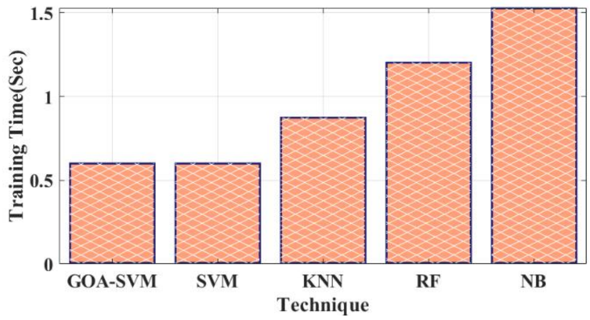

Fig.25. Training Time comparison of proposed GOA-SVM with existing method

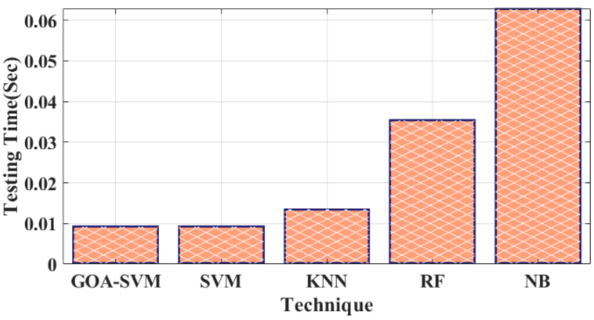

Fig.26. Testing Time comparison of proposed GOA-SVM with existing method

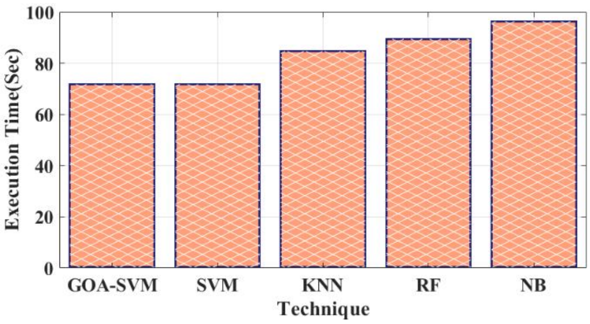

Fig.27. Execution Time comparison of proposed GOA-SVM with existing method

The comparison between the proposed GOA-SVM and existing methods' training times is shown in Figure 25. For GOA-SVM, SVM, KNN, RF, and NB, the training times obtained are 0.601s, 0.601s, 0.876s, 1.20s, and 1.52 seconds. Therefore, compared to the existing approach, the proposed method needs less training time. Figure 26 compares the testing times for the proposed GOA-SVM and existing techniques. For proposed and existing approaches, the running times for testing time are 0.0092s, 0.0092s, 0.0135s, 0.0354s, and 0.0629s. The testing period is shorter than the existing model, as shown in the graphical representation. The execution timings of the proposed and existing approaches are depicted in Figure 27. Execution times for GOA-SVM, SVM, KNN, RF, and NB are 71.73, 71.73, 84.63, and 89.46, respectively. The execution timings for both the proposed and existing approaches are depicted in Figure 27. GOA-SVM, SVM, KNN, RF, and NB have achieved execution times of 71.73, 71.73, 84.63, 89.46, and 96.32, respectively. As a result, performing the proposed method takes less time.

5. Conclusions

Millimeter-wave (mmWave) frequencies are required to be utilized on fifth generation (5G) networks to achieve high rates of data transmission. However, Transmission Control Protocol (TCP) is implemented for many applications to manage data transmission, significantly degrades the performance of these networks. TCP analysis continues to be difficult to perform because of mobility in nature. Because high frequencies are unable to traverse through obstructions, transmission over higher frequencies suffers from blockages and path loss. The TCP speed in 5G mmWave networks is further impacted by these blockages, which lead to increased packet loss probability, longer Round Trip Time (RTT) and Re-transmission time out (RTO) expiry. While using mmWave bands offers wide bandwidth and excellent spectral effectiveness in the channel path, mmWave networks experience considerable channel quality fluctuation because of the signal degradation caused by obstructions. The difficulties in implementing CC in 5G networks can be attributed to blockage issues, beam misalignment, insufficient buffer sizes, frequent handovers, interference because non-data signals are constantly transmitted, and changes in data flow because of the use of edge computing. So, the Wireless TCP congestion prediction model is designed using Rough Set Theory with hypertuned SVM based on the behaviour of network towers for high speed and low latency communication. Initially, data gathered from different towers are analyzed and created as a dataset. In order to create equivalence classes within the given training data, super MICE imputation is used to replace the missing data, and the tower behaviours are then clustered into several classes using rough set theory. Then, using the Gazelle optimization algorithm (GOA) to select the parameter in the best way, the hypertuned SVM classifier learns the parameter to identify the congestion level as low, medium, and high. After determining the level of congestion, the congestion window is automatically changed in the wireless Tower Behaviour based TCP. Performance metrics for the proposed method are compared to those for FCM, KNN, Agglomerative in terms of informedness, Adjusted Rand Index, FM, NMI, jaccard and the congestion level is prediction in terms of accuracy, recall, precision, error, false negative rate (FNR), false positive rate (FPR), F1_score, false discovery rate (FDR), negative predictive value (NPV), false omission rate (FDR), Kappa, and Mathew's correlation coefficient (MCC) are then contrasted with SVM, KNN, RF, and NB. Some of the performance metrics are obtained to show the proposed method performs well by the value attained for accuracy is 93%, precision is 92%, sensitivity is 94%, f1-score is 92%, error is 7%, NPV is 90%, MCC attained as 92% informedness as 91%, Adjusted Rand Index is 0.83, FM is 0.95, NMI is 0.692, jaccard is 0.737 and time taken for training, testing and execution are 0.601s, 0.009s and 71.7s. The result demonstrated that the proposed method is best than other techniques to predict congestion level. In future, possibilities in the creation of various ML-based algorithms with high throughput for the deployment of Congestion Control in advanced 5G and next 6G networks.

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*Conflict of Interest: T*he authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Availability of data and material: Not applicable

Code availability: Not applicable

Author contributions: The corresponding author claims the major contribution of the paper including formulation, analysis and editing. The co-author provides guidance to verify the analysis result and manuscript editing.

Compliance with ethical standards: This article is a completely original work of its authors; it has not been published before and will not be sent to other publications until the journal's editorial board decides not to accept it for publication.

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