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Support Vector Machine Based Traffic Congestion in Intelligent Transportation System

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Abstract: Traffic congestion is one of the most significant obstacles that municipal managers must surmount to be successful in their work. This paper focuses on the use of intelligent transportation systems (ITS) and smart environmental monitoring in smart cities to improve the accuracy and efficiency with which they track and respond to environmental threats such as pollution, traffic jams, and more. The goal of this paper is to classify the traffic congestion using machine learning algorithm and to offer a better congestion management. To make an accurate prediction of congestion using a Support Vector Machine, a pre-processing layer that can manage incomplete values and improve the quality of the incoming data is required. The results of simulation show that the proposed method achieves higher accuracy in detecting the traffic congestion and smartly manages to reduce it.

Keywords: Support Vector Machine, Traffic Congestion, Intelligent Transportation System

1. Introduction

One of the most noticeable characteristics of a smart city is an advanced and interconnected public transportation network (ITS). Today society faces a significant challenge in the form of traffic congestion; however, building new roads in the conventional fashion is not only impossible due to the prohibitive cost involved, but it is also frequently not even possible due to the limitations enforced by both the available land and the financial resources [1].

The immediate implementation of ITS is required to immediately increase the carrying capability of road networks. The combination of slower driving speeds and increased traffic volumes contributes to a further deterioration in the quality of the air, which in turn contributes to a further deterioration in the standard of life. This is occurring because of the two variables working together in conjunction with one another [2].

The government is devoting more resources to research and construction to maximize the potential of the facilities that are already in existence, as well as to reduce the strain that is being placed on the transportation networks, which are in the process of falling apart. Based on a better transportation infrastructure and advanced IT technology, the relationship between vehicles, road networks, and people can be strengthened, thereby improving order and control of the transportation system by making the traffic management system more efficient, convenient, safe, and intelligent [3,4].

The fundamental information that constitutes ITS is made up of all the components that encompass the transportation system. These components include the roadways, the vehicles, and the people who use the system. The information that is gathered from the vehicle is utilized primarily for the purposes of monitoring and gaining an understanding of the operational conditions of the vehicle [5].

These conditions include the vehicle current position as well as the way it is being driven. The current motion situation of a vehicle is determined by several variables, some of which are its location, velocity, heading, the position of the throttle, and the pressure on the brakes. The status of the vehicle is dependent on a variety of factors, such as the make, model, color, number of drivers and/or passengers, and service records of the automobile [6].

It is possible to improve the energy efficiency of a vehicle by first analyzing several variables, such as the vehicle speed, acceleration, throttle use, and stop use, and then providing the driver with the appropriate guidance to improve the vehicle energy efficiency. However, it is difficult to acquire more comprehensive vehicle information since singular characteristic information is insufficient to deal with complicated environments during the process of acquiring position and motion information [7]. This makes it difficult to acquire more information about the vehicle location and motion. Because of this, it is more difficult to obtain additional information regarding the position and motion of the vehicle [8].

The most essential methods for gathering information about roadways are sensing that is carried out by vehicles while they are traveling along them, probing that is carried out by the environment and the roadway itself, and electronic charges. The information that is gathered from all of the different devices that are scattered across the road can be separated into two distinct groups: motionless and moving [9]. With the assistance of a sensing device that is mounted on the vehicle itself, mobile collection technologies can collect data in real time about the movement of traffic along a particular route [10].

The nation highway traffic infrastructure will be improved by the construction of a system that provides situational awareness and dynamic surveillance. This is being done to better serve the driving public. This system will make extensive use of recently developed information network technologies as well as technologies for intelligent network devices. to visualize, regulate, and evaluate the nation highway network, it is essential to set up sensor networks for the national highway traffic infrastructure [11].

If the current state of the road network is assessed first, it will be feasible to build significant sections of interstate and state highways. The system can automatically call for the required services in the event of accidents or other kinds of emergent situations.

Recent advancements in artificial intelligence and machine learning have made it possible for ITS and smart environmental monitoring in smart cities to improve the accuracy and efficiency with which they track and respond to environmental threats such as pollution, traffic jams, and more. In addition to the fact that it makes traffic flow less efficiently and adds to what was already a significant level of environmental pollution, traffic congestion can have a negative effect on the quality of life that people lead [12].

Because of this, gridlock has a negative impact not only on the economy, but also on output, as well as on the quality of living in general. Congestion management is currently the most significant obstacle that municipal managers must surmount to be successful in their work. In an effort to find a solution to the issue, numerous research initiatives have been carried out over the course of the past few decades to find methods that can ease the burden of traffic overcrowding. Both the collection of data on traffic and the development of intelligent transportation systems have progressed over time to find solutions to the problems.

This paper focuses on the use of AI and ML techniques to improve the performance of the transportation system in smart cities. The purpose of this paper is to use the support vector machine (SVM) to detect the traffic in the smart city.

2. Related works

This section includes a presentation of works that are pertinent to the topic of route management, which is also known as the management of vehicular traffic congestion in urban regions. These works were selected because of their relevance to the topic. In recent years, there have been several publications that have tried to address this problem.

Meneguette et al. [13] came up with the idea of using a solution that was based on artificial neural networks (ANN) to improve the accuracy with which congestion levels could be anticipated and to optimize the flow of traffic in metropolitan areas. Intelligent Protocol of Congestion Detection is the term assigned to this solution. The ANN considers the typical speed of vehicles along the road in addition to the number of vehicles per square mile to categorize the traffic and offer alternative routes. However, the solution does not have access to the full plan, and it does not know how to prevent routes from overlapping, which could lead to the formation of a new traffic jam. It was found to be less successful, particularly in settings with a high population density since it does not make use of any broadcast suppression mechanism. This was one of the issues that was found during the investigation.

Younes et al. [4] suggested the use of two different protocols, one of which is known as the V2V and V2I-based Efficient Road Congestion Detection Protocol (ECODE), and the other is known as the intelligent route recommendation protocol, or ICOD for short. Together, these protocols are referred to as the V2V and V2I-based ECODE. Every intersection has what is known as a roadside unit (RSU), and automobiles can talk to one another through a system called V2V to introduce themselves to other vehicles in the area. When a vehicle receives an ADV, the information that it receives is added to a database that is referred to as the neighbor report table. This table is then used to generate a traffic monitoring report (TMR) that specifies information about the road, such as its average speed, its density, and the anticipated time it will take to complete the journey. An additional advantage of the operation is that the TMR is transported to any RSU by the vehicle that is situated in the region of the world that is immediately adjacent to it. Once it has been provided with the TMR, the RSU will, prior to sending out a RecommendReport message, analyze its own data to determine the route that will get it to each location as quickly and effectively as possible. Following the receipt of a RecomReport message, a vehicle will, as the final step, reroute itself to the location in question and then, in a single hop, transmit that message to the vehicles that are located closest to it.

Doolan et al. [15] suggested EcoTrec as a routing strategy, with the goal of reducing CO2 emissions while keeping the same amount of travel time. This was done to maintain the same amount of travel time. This is achieved by having each car exchange information about its location, speed, and the quantity of gasoline it is consuming at regular intervals. As a result, EcoTrec conducts an analysis of the state of the roads, and then, using a decentralized approach, it allows each vehicle to choose its own path. EcoTrec will occasionally and at random designate the second-best route to certain vehicles to prevent those vehicles from receiving credit for always taking the optimal route.

Wang et al. [16] came up with the idea of the Next Road Rerouting (NRR) solution to reduce on the amount of time spent idling in traffic in highly populated metropolitan areas. to determine the path that will result in the lowest overall cost, NRR employs an algorithm that is predicated on a cost function. This function considers a wide range of considerations, such as the number of vehicles on the road, the journey time, the distance to the location, and the percentage of the road that is congested. There are two different phases involved in the process of planning the routes that vehicles will take. First, the iTL module examines each of the pathways that it is in control of to see if any of them have a backup. If there isn't one, then the module moves on to the next one. If traffic becomes gridlocked, iTL will flashlights in the direction of approaching vehicles to get their attention. Information on alternative routes to get to iTL has been requested by vehicles that are presently using this route. However, for this system to work correctly, an iTL device needs to be installed at each intersection to collect data regarding the flow of traffic. This data can then be analyzed. In addition, FoxS can function correctly even when there is no active Internet connection, in contrast to NRR, which requires an active Internet connection to perform correctly.

Cloud-based traffic optimization system proposed by Jeong et al. [17] as a self-adaptive interactive navigation tool (SAINT). to make the movement of traffic more efficient, the vehicles that are connected to this system send data to a traffic management center that is in the cloud. For the RSU in the vehicle and the eNodeB in the cellular network to be able to communicate with the cloud, it is essential for both to have Internet connectivity. This can be accomplished through an 802.11p connection or a 4G connection. The possibility of a route becoming extremely popular and causing new levels of congestion has been substantially reduced. This is because there are now fewer people using the route. Vehicles are required to make use of their Internet connections to guarantee that the cloud is kept continuously up to date on the conditions of the routes that they travel. The Dedicated Short-Range Communications (DSRC) standard, which is the preferred method of communication for vehicles, does not have any mechanism that enables it to function correctly in high-density situations like those that are found in metropolitan centers. This is because DSRC was not designed to work in environments with a lot of people and vehicles near one another.

3. Proposed Method

We use a process that can be broken down into four phases, each of which is illustrated in Figure 1, to classify the traffic based on the results of machine learning. The procedure starts with the gathering of data and the selection of features, then moves on to the preprocessing step, a deep learning model, and, ultimately, the visualization of the findings.

After going to great lengths to acquire data and after determining which variables are most significant, a dataset is constructed by using samples of actual traffic flows. This comes after first going to great lengths to acquire data. Before classifying each sample according to the appropriate category, we remove any data that we consider to be irrelevant through a filtering process. The characteristics were put through a standardization procedure during the preprocessing phase, which resulted in a more uniform appearance. The SVM algorithms build the traffic classification model by utilizing the training information that was previously provided.

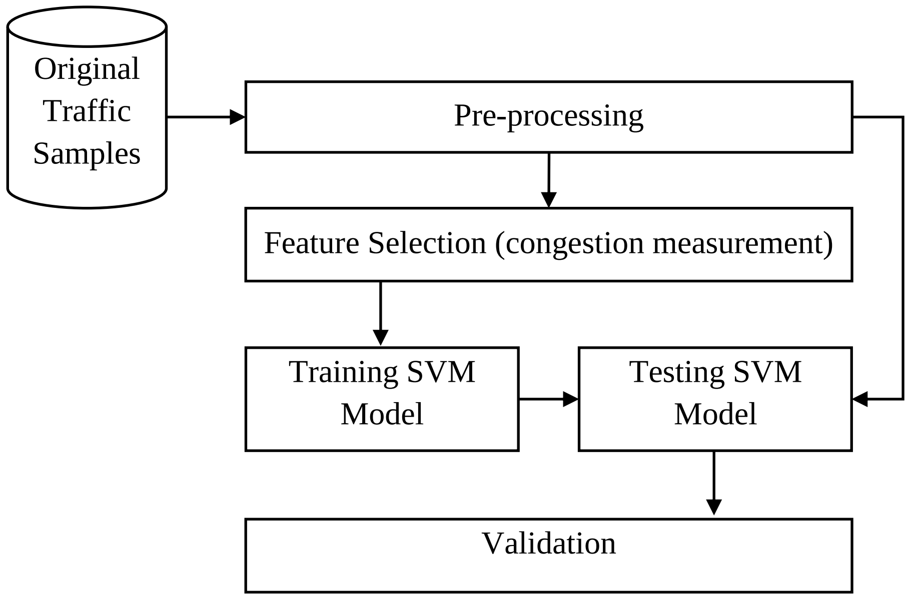

Figure 1: Proposed Model

3.1. Preprocessing

Cleaning up the data is an essential step that needs to be completed before moving on to analyze the data. The outcomes of the cleaning have a connection to the overall performance of the model as well as the implications that are generated by it. In most investigations, the process of cleansing the data consumes between 50 and 80% of the total amount of time that is invested in the investigation. In this instance, to clear the accumulated driving-track records of any unwanted noise, we smooth the data through the application of the moving-average method. We use something that called dispersion standardization as a method for cleaning up the data so that it can be used for navigation.
We employ a method known as moving average to clean up the historical driving-track data and produce a trajectory graph that is more uniform in shape. Using the moving average technique, one takes the total number of observations from the seconds before and after the current one and adds one to that total. This allows one to arrive at the result that has been filtered for the present moment. We anticipate that the noise will have a mean value of zero, a standard deviation value of two, and a variance σ^2.
$g_t = x_t + \varepsilon_t$
where
x_t - observed value,
g_t - true value and
ε_t - noise.
The data that are collected at each succeeding interval are added together and then averaged to reduce the significance of changes that are caused by chance.

3.2. Congestion Measurement

There are a variety of different measures of congestion that have been developed, each of which takes into consideration its own set of performance criteria to quantify the degree of congestion that exists. The following criteria make it possible to classify strategies for alleviating congestion into five separate categories:

3.2.1. Speed

Speed Reduction Index (SRI): The Speed Reduction Index (SRI) is the ratio of the relative speed shift that takes place between scenarios in which there is congestion and scenarios in which there is free movement of traffic. A tenfold increase in the SRI ratio has been implemented to maintain the SRI number within the range of 0 to 10. When the indicator approaches a level of 4 or 5, a significant delay in the flow of traffic can be expected. When there is not going to be any congestion, the number ought to be smaller than 4.
$\mathrm{SRI} = (1 - v_{ac}/v_{ff}) \times 10$,
where
SRI - speed reduction index,
v_{ac} - travel speed, and

v_{ff} - free-flow speed.
The free flowing is the average speed during non-rush hours when there is little to no substantial congestion in the roadways. The limit that can be placed on the absolute maximum speed is roughly analogous to the flow rate that develops on its own.
Speed Performance Index (SPI): The Speed Performance Index (SPI) is a tool that was developed to evaluate how effectively different forms of transportation flow through urban areas with heavy traffic. The figure that represents the SPI is arrived at by comparing the driver current speed to the absolute maximum that is permitted by law. The severity of the traffic situation can be assessed on one of three distinct degrees by using this indicator.
$\text{SPI} = (v_{avg}/v_{max}) \times 100$,
where
SPI - speed performance index,
v_{avg} - average travel speed, and
v_{max} - maximum road speed.

3.2.2. Travel Rate

It is possible to determine the travel rate for a specific portion of a journey or route by taking the total amount of time spent commuting and dividing that number by the total distance that has been covered. Utilizing the inverse of speed is another method that can be utilized to ascertain the rate of movement.

3.2.3. Delay

Delay Rate: The delay rate measures the amount of time that is wasted on average per vehicle per hour because of congestion on a specific section of roadway or journey.
$D_r = Tr_{ac} – Tr_{ap}$,
where,
D_r - delay rate,
Tr_{ac} - actual travel rate, and
Tr_{ap} - acceptable travel rate.
Delay Ratio: The delay ratio can be calculated by dividing the delay rate by the actual journey speed to get the answer. The delay ratio can then be determined using this information. It is a method for determining the actual amount of traffic on several different routes, and there are a few different ways it can be done.

3.2.4. Level of Services (LoS)

The LoS method is used in the computations that are included in the Highway Capacity Manual. (HCM). The level of service, also known as LoS, can be determined based on several different variables, including the peak service flow rate, the amount of traffic, its speed, and the ratio of its amount to its capability. The formula for the vehicle-to-capacity ratio, which can be written as
$\text{V/C} = N_{v/}N_{max}$,
where,
N_v - spatial mean volume, and
N_{max} - maximum vehicles and it is expressed as:
$N_{max} = (L_s/L_v) \times N_l$
where
L_s - spatial length of the segment,
L_v - average length of the vehicle, and
N_l – total lanes.
L_v - safety distance and vehicle length.

3.2.5. Congestion Indices

Relative Congestion Index (RCI): The RCI is responsible for determining the degree of congestion (T_{ff}); it does this by comparing the amount of time spent sitting in a traffic jam to the amount of time that was spent commuting without any interruptions. A RCI of 0 indicates a level of congestion that is regarded as being low, whereas an RCI of more than 2 indicates a level of congestion that is regarded as being high.
$\text{RCI} = (T_{ac} - T_{ff})/T_{ff}$
where
T_{ac} - actual travel time.
The ratio of the spatial length to the spatial mean speed is another method that can be used to further quantify this ratio. The RCI is the ratio of the actual journey time, which is referred to as Tac, to the highest possible theoretical transit time. To determine the free-flow transit time (T_{ff}), simply reduce the total distance traveled by the average speed at which it was traveled. This will result in the calculation.

Road Segment Congestion Index (R_i): One method for determining the level of congestion that occurs on a specific road segment is to compare the amount of time that was spent on the road segment during the observation period in a state that was not congested to the typical state of the road segment. The indicator Ri is used to show the results of this comparison. If the speed performance indicator (SPI) for the traffic condition in question is greater than 50, then that traffic condition is not regarded as being overcrowded. If the R_i number is low, then the degree of congestion along that stretch of road is likely to be high. The value of the R_i indicator can be anywhere from 0 to 1 at any given time.

$R_i = (\mathrm{SPI}_{avg}/100) \times R_{NC}$,

$R_{NC} = t_{NC}/t_t$,

where

R_i - congestion index in the road segment,

SPI_{avg} - average speed index.

R_{NC} - non-congested state proportion

t_{NC} - non-congested state duration.

t_t - observation length.

3.3. SVM Classification

Support vector machines are frequently used as classification methods for a wide variety of data types, including human motion, visual and auditory stimuli, and other forms of data. By constructing an optimum separation hyperplane in a high-dimensional feature space, SVMs uses differentiation between a number of distinct categories of objects. The mapping of these components into this space makes use of non-linear functions.

It is possible to find a solution to the nonlinear separable problem by first projecting the input space onto a high-dimensional feature space and then identifying the separation hyperplane that the projection produces. If we are looking for a hyperplane that can differentiate between groups in a dependable fashion, we need to search for the one that has the largest gap (or clearing) between the groups it differentiates. This will allow us to find a hyperplane that meets our requirements.

The training algorithm in support vector machines (SVM) is reformulated as a problem to be addressed by quadratic programming (QP), which is a technique that possesses a solution that is universally recognized. Taking into account the training set

$(x1,y1), \ldots, (xm,ym) \in R^N \times \{-1,+1\}$,

where

xi - input value and

yi - assigned class.

If the data cannot be separated linearly, a process of non-linear mapping known as RNRM is carried out within the new feature space RM to accomplish the desired result of linearly separating the data. RNRM is an abbreviation for reverse non-linear mapping. The resulting hyperplane of separation between object classes can be understood as the equation $\phi: R^N \to R^M$, where R^M suggest to the relationship that exists between the two variables.

$\omega \cdot \phi(x) + b = 0$,

where $\omega \in RM$ and $b \in R$

4. Results and Discussions

The training of a support vector machine typically calls for a sizeable quantity of data, and the process of collecting and annotating this data can be quite time-consuming and costly. In the absence of appropriate training data, SVM models run the risk of improperly fitting the data, which can lead to poor learning and generalization. This risk increases as the amount of training data decreases.

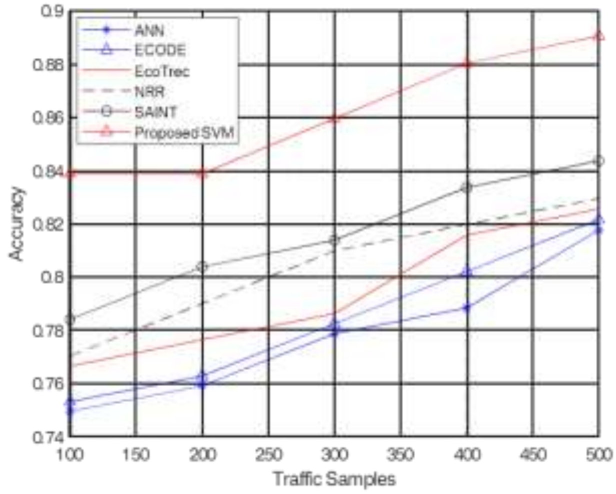

Figure 2: Accuracy

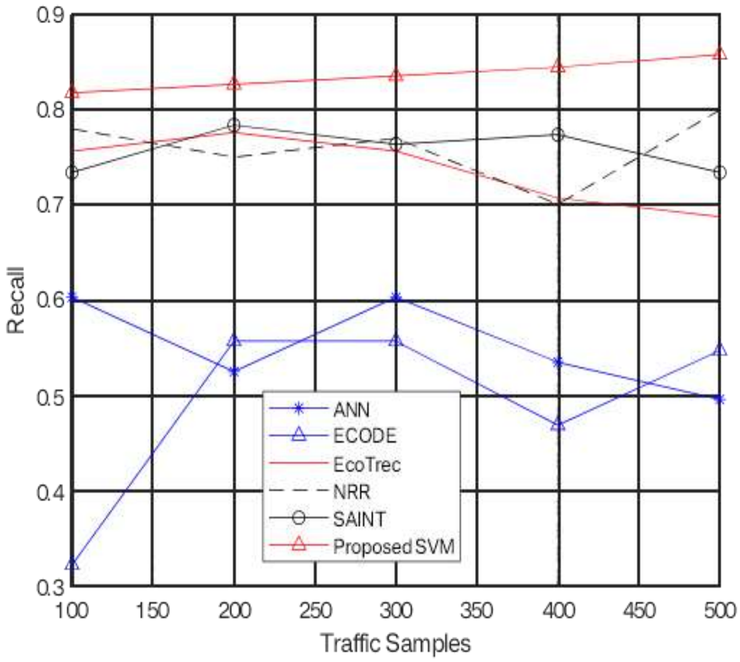

Figure 3: Recall

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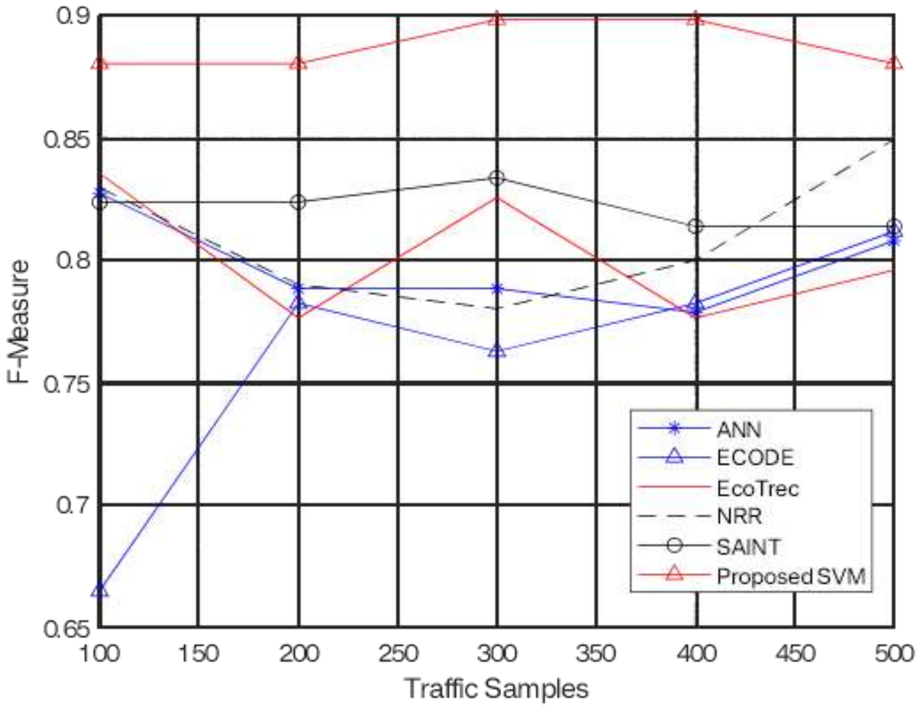

Figure 4: F-Measure

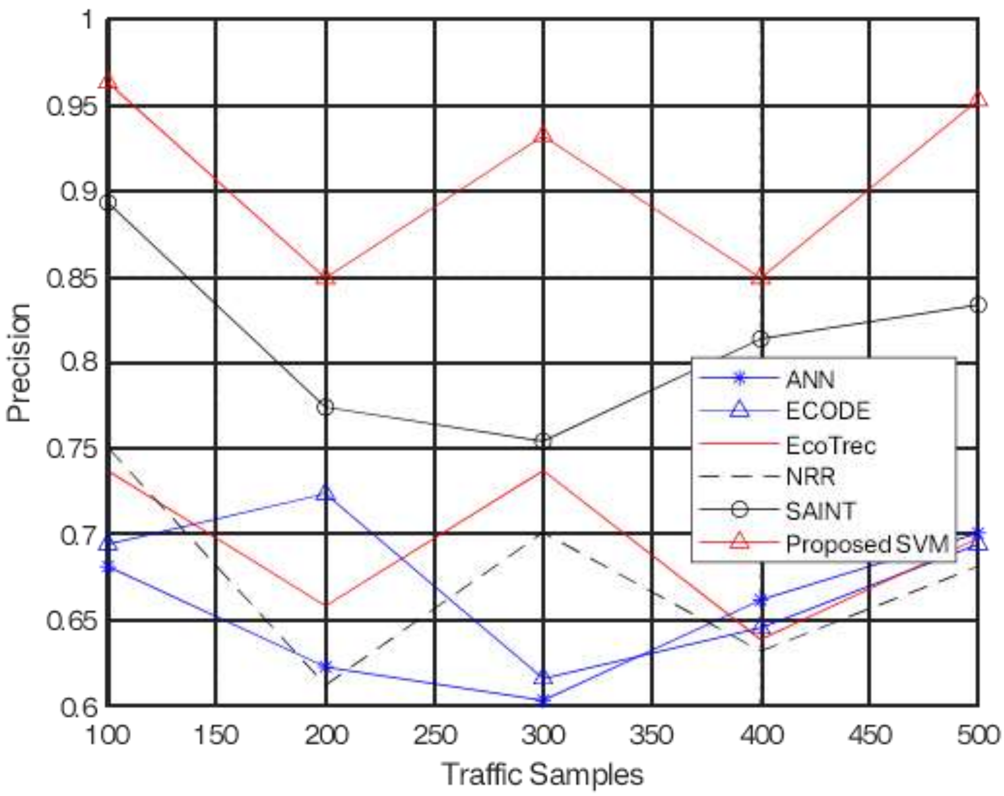

Figure 5: Precision

From the results, it is found that the proposed method classifies well the traffic congestion instances than the existing methods as in Figure 2-5. It may be difficult to collect sufficient data, specifically annotated data, for applications. One strategy that can be used to address this problem is known as the transferring representations learned from a source task to the current task strategy. This is made feasible by the fact that the characteristics that are learned by earlier layers of a network are frequently very generalizable and applicable in a variety of different settings.

5. Conclusions

In this article, a support vector machine (SVM) model is suggested for use in an intelligent traffic control system with the goal of predicting the occurrence of traffic congestion. This model will be implemented in an intelligent traffic control system. To make an accurate prediction of congestion using a Support Vector Machine, a preprocessing layer that can manage incomplete values and improve the quality of the incoming data is required. Additionally contributing to an increase in the projections' level of precision is this layer. It would appear, on the basis of the outcomes of the simulation evaluation, that the proposed SVM model performs significantly better than the baseline methods.

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