Contemporary Study of Machine Learning Algorithms for Traffic Density Estimation in Intelligent Transportation Systems

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Intelligent Transportation Systems (ITS) provides the state-of-the-art real time integration of vehicles and intelligent systems. Collectively, the prospective of the technologies have capability to communicate between system users, roads, and infrastructure. This study presents a comprehensive examination of many applications and implications of AI and ML in the development of an ITS. The primary objective of this is to effectively mitigate the traffic congestion and enhance road safety measures to prevent accidents. Subsequently, we examined different machine learning methodologies employed in the identification of road traffic based on vehicles and their junctions with the purpose of evading impediments, as well as forecasting real-time traffic patterns to attain intelligent and effective transportation systems. The exponential growth of the population inside the country has resulted in a corresponding rise in the utilization of vehicles and various modes of transportation, thereby it needs a contributing to the exacerbation of traffic congestion and the occurrence of road accidents. Therefore, there exists a need for intelligent transportation systems that possess the capability to offer the dependable transportation services while simultaneously upholding environmental standards to overcome the traffic congestions. Designing accurate models for predicting traffic density is a crucial task in the field of transportation systems. This study compares the ML models which are derived using a variety of machine-learning approaches. Supervised machine learning algorithms, including Naive Bayes, Markov models, KNN, linear regression, and SVM, and KNN are employed. The conclusion result suggests that the Markov model achieves the highest level of accuracy, of 98%. Implementation of ITS with Markov Model provides the best performance in resilient environment.

Abbreviations
Machine learning (ML)
Reinforcement Learning (RL)
k-Nearest Neighbor (K-NN)
Intelligent Transportation Systems (ITS)
Convolutional Neural Networks (CNNs)
Deep Convolutional Neural Networks (DCNNs)
Naive Bayes (NB)
Data Mining (DM)

Keywords: Machine learning; intelligent transportation systems; traffic density estimations; artificial intelligence; naïve bays; markov model; KNN.

Introduction:

In recent years, there has been a growing interest in ITS. The rapid advancement of vehicle computing hardware, vehicular sensors, and urban infrastructures has led to the emergence of numerous noteworthy applications within the field of ITS. The most recent developments in AI and ML have facilitated the implementation of ITS and smart environmental monitoring systems in smart cities. These technologies provide a more accurate monitoring of the elements that influence the environment, allowing for optimal control of pollution, traffic congestion, and other detrimental consequences. The impact of traffic congestion on individuals' quality of life is evident through its adverse effects on traffic efficiency and the exacerbation of environmental pollutants. Therefore, traffic congestion exerts an influence on the country's output, economic development, and human activities. One of the most critical concerns in the field of urban planning is around the identification of effective strategies to tackle the problem of traffic congestion [1]. The management of traffic congestion has been a prominent subject of academic inquiry, with numerous solutions arising from various research endeavors conducted in this sector over the past few decades [2]. Over the course of time, there has been a notable evolution in the field of traffic data gathering and intelligent transportation systems, which can be attributed to the aforementioned concerns [3]. In a correlated advancement, there has been a significant increase in the adoption of ML techniques. ML has been extensively utilized in a diverse range of applications, all of which are quite similar to ITS and require a thorough set of prerequisites. Machine learning techniques, specifically deep learning and reinforcement learning, supervised learning, unsupervised learning have demonstrated their utility in analyzing extensive datasets to identify patterns and underlying structures as shown in Figure 2. This capability is crucial for precise prediction, informed decision-making, and safeguarding vehicles against cyber-attacks. A dataset that encompasses information on scientific publications spanning the past few decades. Figure1 shows the design requirements for ITS architectures that are applicable to any application, i.e. data collection, data aggregation and data processing, it is possible to reduce certain requirements while working with ITS.

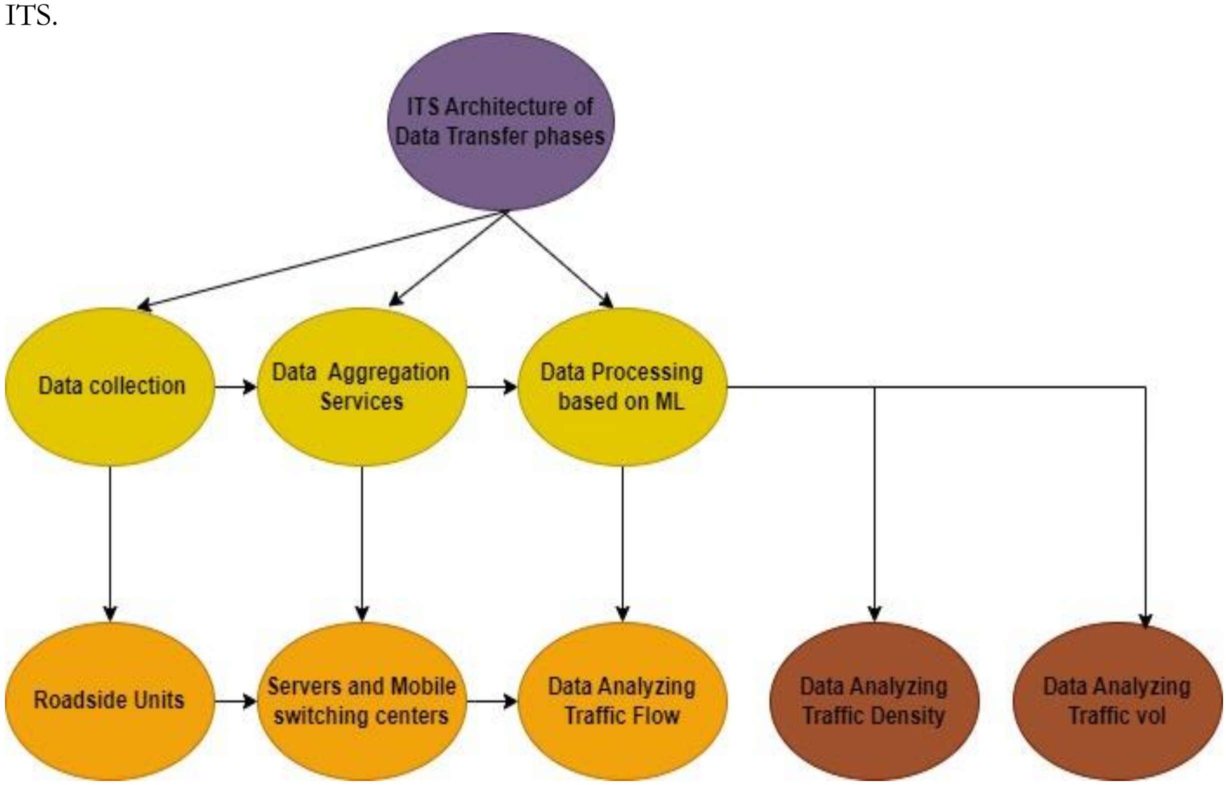

Figure 1. ITS architecture in data transfer phases

ITS encompass the integration of cutting-edge technology, such as machine learning methodologies, with the aim of augmenting transportation efficacy, safety, and sustainability. The machine learning approaches that are frequently employed in ITS, like the prediction of traffic flow: Machine learning techniques including artificial neural networks, support vector machines, and random forests, have the capability to assess past traffic data so as to forecast forthcoming traffic circumstances. The provided information serves to enhance the optimization of traffic signal timings, facilitate the implementation of dynamic route guidance, and enhance overall traffic management. Reinforcement learning algorithms possess the capability to acquire and adjust traffic signal management rules with the objective of optimizing traffic flow efficiency, mitigating congestion, and minimizing trip time. Machine learning algorithms can assess and identify driver behavior patterns by analyzing data gathered from diverse in-vehicle sensors like accelerometers, speedometers, and cameras. This includes the identification of aggressive driving tendencies, detection of drowsiness, and recognition of instances of driver distraction. The aforementioned data can be utilized for the development of driver feedback systems, insurance-related applications, and the enhancement of overall road safety to the optimization of public transportation can be achieved through the ML based methods are also capable of estimating passenger demand, establishing optimal schedules, and enhancing fleet management to optimize public transportation. By integrating historical ridership trends, weather conditions, and special events data, these algorithms have the potential to enhance the efficiency and efficacy of public transportation systems. The above data represents a limited selection of machine learning methodologies employed within the realm of intelligent transportation systems. With the continuous advancement of technology, the use of machine learning is expected to assume a progressively significant part in the transformation of transportation, leading to enhanced safety, efficiency, and sustainability within the system.

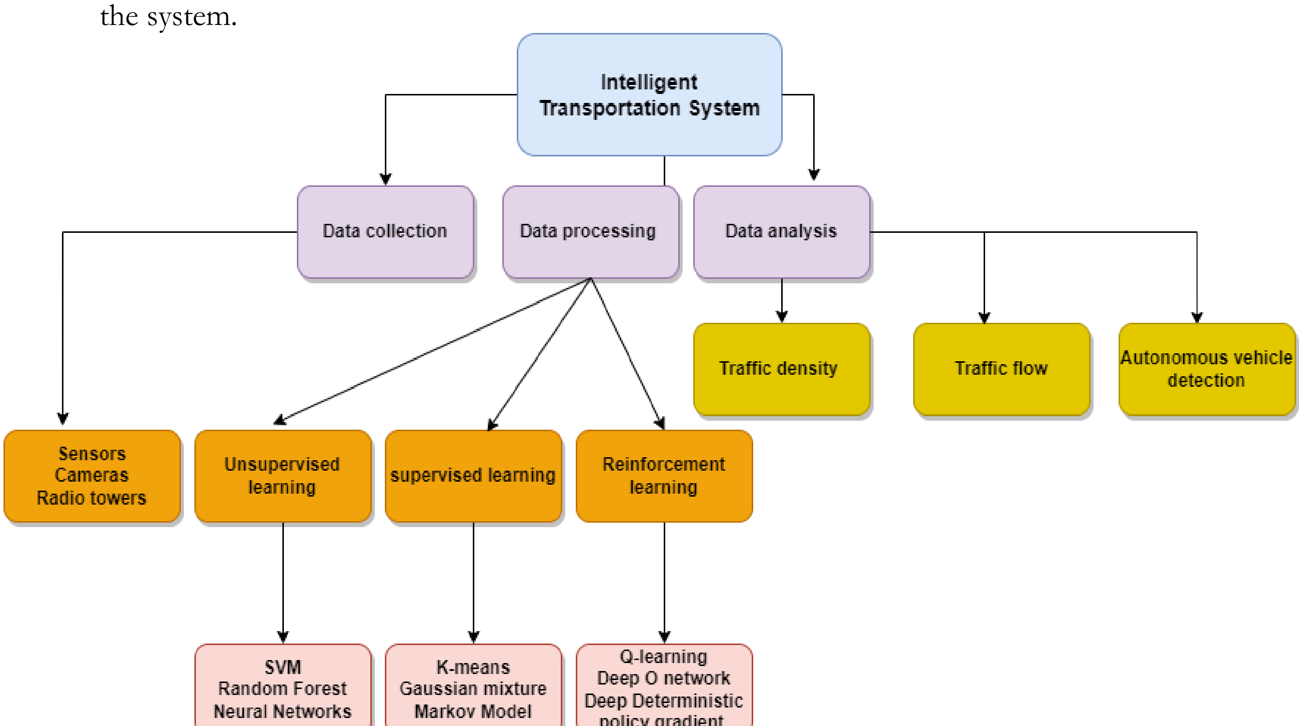

Figure 2. Machine learning based algorithms

Machine Learning Techniques used in ITS:

In literature the authors primarily examine standard ML methodologies, encompassing SL, UL, RL, and DL. Data is a prominent commodity that is taken from contemporary ITS. Data can be acquired from all layers of ITS due to the varying scopes of ITS applications, which encompass global, local, and hybrid applications. The data-intensive nature of ITS facilitates the intrinsic capacity of ML to extract information from data. ML offers a range of capabilities such as regression, classification, prediction, clustering, and decision-making. These features have the potential to enhance ITS and serve as the fundamental building blocks for various tasks within ITS applications. This section examines two main aspects: 1) the integration of ML within ITS through the utilization of an ML pipeline; and 2) the utilization of ML in various activities performed by ITS. Machine learning techniques are commonly categorized into three distinct classes, depending on the availability of labeled attribute information within a given dataset. These classes include unsupervised learning, supervised learning, and semi-supervised learning. The utilization of machine learning techniques in conjunction with IoT devices has emerged as a significant catalyst propelling advancements in the wireless industry, particularly in the forthcoming fifth-generation (5G) technology [4].

Supervised Learning:

The framework of supervised learning establishes connections and interdependencies between the expected outcome and input characteristics. This process entails creating a classification or regression model by drawing inferences from a labeled training dataset. A training dataset consists of instances that are utilized for the purpose of learning. Labeled data refers to a collection of samples that have been annotated or tagged with corresponding target variables. SL has the capability to make predictions for fresh data by utilizing the function acquired from the training data. Based on their respective roles, the majority of supervised learning algorithms can be categorized into two primary classifications: Classification algorithms acquire the ability to forecast a specific category as a consequent for a novel observation, relying on labeled training data.

Unsupervised Learning:

Unsupervised learning is a methodology for knowledge discovery that relies on data analysis to deduce the underlying structure of datasets containing input data without labeled answers. The algorithm acquires knowledge of patterns and correlations within the data without the presence of pre-established labels or categories. This implies that the algorithm autonomously investigates the data in order to discern concealed structures and patterns. This technique finds applications in various domains, such as clustering, anomaly detection, and dimensionality reduction. Unsupervised learning proves to be highly advantageous in scenarios involving extensive datasets and situations where the anticipated result is not predetermined. These methods encompass various techniques, common protypes include clustering algorithms in data analysis for instance KNN, hierarchical clustering, and principal analysis.

Reinforcement Learning:

The ability to choose amongst multiple options is one of the most important skills that can be acquired through the process of reinforced learning within a given environment with the goal of optimizing the overall sum of rewards obtained. RL has the capability to engage in zero-shot learning, wherein it can initiate the learning process without any prior data. RL is a specialized domain within the study of machine learning, which focuses on the development of algorithms that enable agents to acquire decision-making abilities in intricate and ever-changing settings. In the domain of intelligent transportation systems, they optimize the route planning, and improve traffic light control. Reinforcement learning agents has the capability to adapt to dynamic traffic situations and acquire the ability to make decisions that effectively mitigate congestion and enhance journey durations through the process of trial-and-error learning.

Decision Trees:

Decision trees are hierarchical structures used for the purpose of classification tasks in machine learning applications. They serve as a visual representation of a decision-making process that encompasses multiple potential outcomes. The construction of a decision tree follows a top-down approach and comprises several nodes. Each node in the tree can either represent a class or a condition that guides the classification of a testing item. The utilization of a simplistic methodology in addressing categorization problems. At each level of a decision tree, a classification sub-process occurs, wherein the primary work is divided into smaller sub-tasks. [5] conducted an experiment to evaluate the performance of a decision tree in comparison to four other machine learning algorithms (Random Forest, Multilayer Perceptron, Support Vector Machine, and Logistic Regression) for the purpose of predicting traffic congestion. The decision tree approach demonstrated comparable performance to the other algorithms in terms of precision, recall, and accuracy. However, logistic regression exhibited a little superior performance.

Clustering:

Clustering is an unsupervised method for classifying objects into distinct groups based on their similarities or recognized patterns. Clustering, unlike classification methods, does not require known labels for model training. Authors of [6] propose using Fuzzy C-Means clustering to generate short-term traffic predictions. In contrast to conventional clustering methods, where instances are assigned exclusively to a single class, the Fuzzy C-Means algorithm permits for partial membership of instances to several classes. The membership function is used to define this specific level. The authors of this research employ a traffic simulator that incorporates authentic traffic data collected from Japan's road network. The authors conducted a comparative analysis of the Fuzzy C-Means method and the k-Nearest Neighbour (K-NN) technique, which will be elucidated upon in the section on instance-based algorithms. The proposed method reduces the error rate by approximately 26% when compared to the K-NN algorithm. We have compared the five machine learning algorithms for traffic estimations in intelligent transportation systems.

Literature Review:

Researchers have given a significant amount of attention to the topic of intelligent transportation due to the fact that it can be applied to the solution of a wide range of everyday problems and has an effect on the formation of modern smart cities. In addition, they have the potential to be usefully applied due to the intrinsic characteristics of the issues that are being addressed. This review has two primary goals: first, to identify the prevalent pattern in the application of ML and IoT technologies in the field of smart transportation, and second, to investigate the breadth of research coverage that exists within each distinct subfield of smart transportation. Both of these goals will be accomplished through the examination of the relevant literature. The primary objective of this study is to examine the latest research studies that pertain to various aspects of smart transportation, including route optimization, parking management, traffic light control, accident detection and prevention, identification of road anomalies, and infrastructure development. These studies mostly employ IoT and/or ML approaches. In recent years, traffic forecasting has emerged as a prominent research area within the fields of urban planning and ITS. The research community primarily directs its attention on the identification and analysis of traffic conditions, namely on expressways and metropolitan trunk highways, within the context of traffic-oriented issues. Deep learning algorithms that utilize CNN have been employed as described in [7]. CNN are extensively employed in scholarly works for the purpose of image recognition. The basic structure of an ANN, which includes an input layer, an output layer, and one or more hidden layers, allows for the classification of a CNN as a type of ANN. Pooling, convolutional, non-linear, subsampling, and FC layers are some of the hidden strata that are contained inside the architecture of a CNN. Other types of layers include FC, subsampling, and non-linear. The input data passes through a process that allows features to be learned and acquired while it is being processed by the convolutional layers. The weight and bias values are included as part of the characteristics or parameters. The fact that multiple neurons in a CNN make use of the same filters is one of the most remarkable characteristics of CNNs. Neurons are discrete components that apply a transfer function to the weighted summation of the signals that they receive as input [8]. Following the convolutional layers is a succession of non-linear layers, each of which experience a change by inverting all of the negative values to their positive counterparts. Utilizing sub-sampling layers as the next step in the dimensionality reduction process is the following step. The classification of the input data is accomplished using an FC layer, which is fundamentally the same as a Multi-Layer Perceptron. The information obtained from the smart cameras is analyzed by the researchers, who make use of CNN technique to determine how full a parking lot is. A Raspberry Pi 2 plays the role of the central controller in the entire system implementation. The primary method employed for the smart cameras is utilizing a modified AlexNet model, which has been tailored for this specific purpose. The authors conducted an analysis using a dataset they generated themselves, along with a widely recognized dataset [10]. The findings of the evaluation indicated that the datasets in question had an accuracy of 98.27% and 90.13 %, respectively. Additionally, a thorough investigation of deep learning methods involving CNNs and DCNNs was carried out in reference [11]. The author provided a summary of research works that primarily focus on the application of deep learning algorithms for the detection of pavement degradation. The works being assessed utilize CNN and DCNN techniques on various image datasets, encompassing Google Street View pictures, smartphone photos, and 3D images generated through specialized hardware like GPR [12]. Literature highlights the commendable performance of both CNN and DCNN in the classification of pavement images. Markov models are a type of stochastic sequence model that relies on the utilization of probability distributions. The distribution of probabilities for a parameter within a Markov chain that experiences stochastic transitions over time is totally controlled by the distribution of the variable's prior state. This is because the Markov chain itself is a stochastic process. The HMM is an algorithm that has some characteristics in common with a Markov chain, but it also has latent states that allow for more nuanced adjustments. The states are each represented by a probabilistic function that is derived from the state under consideration. It is possible to define the properties of HMM by taking into consideration the following three factors: the total number of hidden states, the probability distribution that drives state transitions, and the number of system outputs [13]. In reference [14] during the implementation of a cooperative vehicle observation system, the authors explored the challenge of deducing the planned path of travel from the available information. Vehicles that use cooperative sensing have a longer perception range, which results in improved perception quality and sufficient response time for autonomous operation. The utilization of cooperative sensing in motor vehicles makes this outcome conceivable. An application in its condensed form is used in a way that this goal can be accomplished. The model is "trained" by first acquiring speed data, which is then used to train the model using a range of different driving profiles from a collection of cars. These driving profiles are used to train the model. A modified form of the HMM, known as the linked HMM, is an extremely useful tool for analyzing situations that involve a large number of simultaneous processes.

Table 1. ITS prediction based on ML

Year	Ref	Method	Data	Prediction	Simulator
2022	[15]	YOLO3, SSD	Images	Vehicle detection	Not specified
2022	[16]	LSTM	Real time data	Traffic speed	Mathematical model
2020	[17]	Federated learning	Real time data	Traffic flow	Camera images
2014	[18]	K-nearest neighbor	Real time data	Traffic flow	Loop detector
2014	[19]	K-nearest neighbor	Random data	Traffic volume	Network simulator-2
2019	[20]	ANN	Real time data	Traffic density	Camera image
2019	[21]	Lyapunov functions	Random data	Traffic density	VISSIM

2017	[22]	Hybrid observer	Random data	Traffic density	VISSIM
2016	[23]	Kolmogorov Smirnov	Real time data	Traffic condition	Mathematical model
2019	[24]	Lighthill-Whitham	Real time data	Traffic Density	Mathematical model
2022	[5]	YOLO2, CNN	Real time data	Traffic Flow	Camera images
2021	[25]	YOLO3, CNN	Real time data	Vehicle detection	CCTV cameras
2022	[26]	CCNN	Real time data	Traffic density	Camera images
2023	[6]	Markov based method	Random data	Traffic density	Omnet++, SUMO+VISSIM

Material and Methods:

Investigation Site:

The main scope is the comparison of five machine learning algorithms by implementing these machine learning Algorithms on the same data set. The study presents a comparative examination of contemporary object detectors, visual features, and classification models that are applicable in the context of traffic state estimations. Five visual features are investigated successively using four machine learning techniques in order to achieve classification objectives. This section provides a comprehensive analysis of machine algorithms and their applications. The complete flow of the methodology also shown in Figure 3. Table 1 provides a comprehensive summary of the collective findings derived from the literature review. It presents pertinent information such as the name of each algorithm, the frequency of its utilization year in the literature, the method's specific kind, and the corresponding learning type associated with each algorithm. The data that was taken into account consisted of live camera images captured at various days and times. In the evaluation process, both random and average values were utilized while accounting for outliers and missing data points. We have implemented these machine learning algorithms and identified their vehicles speed, accelerations and detection of vehicles with their vehicle IDs their respective junctions, as mentioned in Table 2, which represents the Markov implementation values with respect to vehicles, naïve bays, shown in Table 3 and Table 4 represents the SVM, and Figure 5 values shows the Linear regression, Figure 6 represents the k means clustering implementation.

Markov Models:

Markov Models are mathematical models that represents the sequences by including stochastic processes and probability distributions. Markov model employs on hidden states to enhance its performance. Each state is represented by its corresponding probability function. The properties of a HMM can be ascertained based on three factors: The quantity of hidden variable, and the number of observable outputs, and the probability distribution of state transitions [15]. The authors in [24] examine the topic of motion intention inference by using measures to enhance cooperative vehicle sensing. By using cooperative sensing, the operational range of the vehicle's perception is extended, leading to enhanced perceptual accuracy and adequate time for autonomous actions to be initiated. It is an alternative instantiation of the Markov Model. In [8], authors proposed an algorithm for group routing proposal is based on MDPs. Instead of ascertaining the most efficient path for an individual vehicle, the proposal is to employ group navigation strategies that leverage vehicle similarities and vehicle-to-vehicle communication in order to mitigate traffic congestion. It is commonly recognized as a robust paradigm for tackling optimization and decision-making challenges. Similar to Markov chains, this methodology integrates two additional components. This comprises a set of activities that possess the capacity to result in a particular state. The use of many networks to monitor intelligent public transportation systems is crucial for maintaining continuous and secure operations, safeguarded against unauthorized intrusions [6].

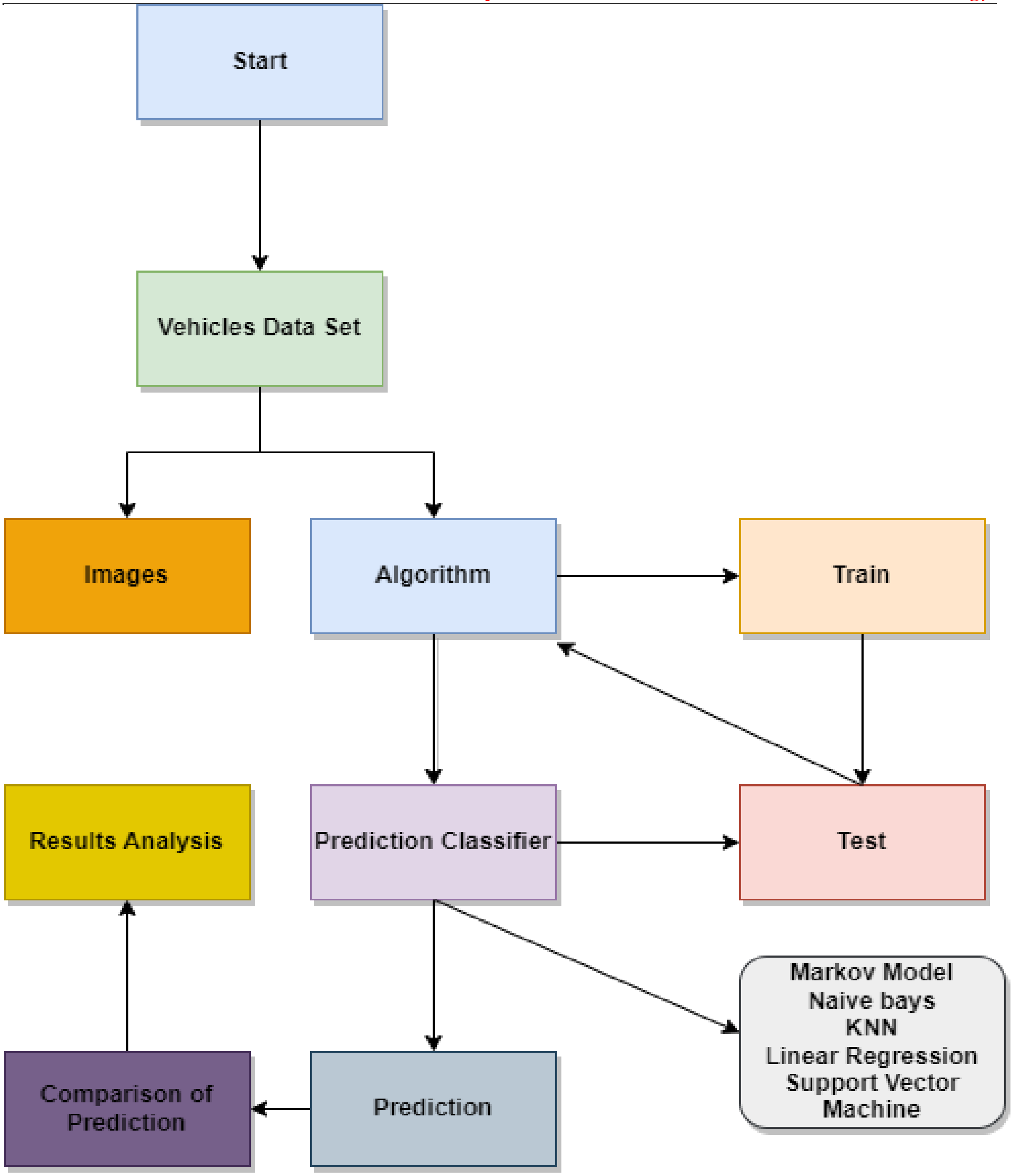

Figure 3. Flow of methodology diagram.

Table 2. Markov model-based junctions, and respective Vehicles IDs

Vehicle 0	0.669410	0.157750	0.846154
Vehicle 1	0.129630	0.314815	0.555556
Vehicle 2	0.6777	0.181189	0.141079
Vehicle 3	0.718539	0.139378	0.776699
Vehicle 4	0.813350	0.103832	0.082818

Naïve Bays:

The Bayes' theorem is considered to be the basis of the Naive Bayes (NB) algorithm. Researchers presented the idea of a comprehensive road traffic safety system that would encompass everything from data storage to analysis. The analysis method for this system would primarily be based on Bayes' theorem.

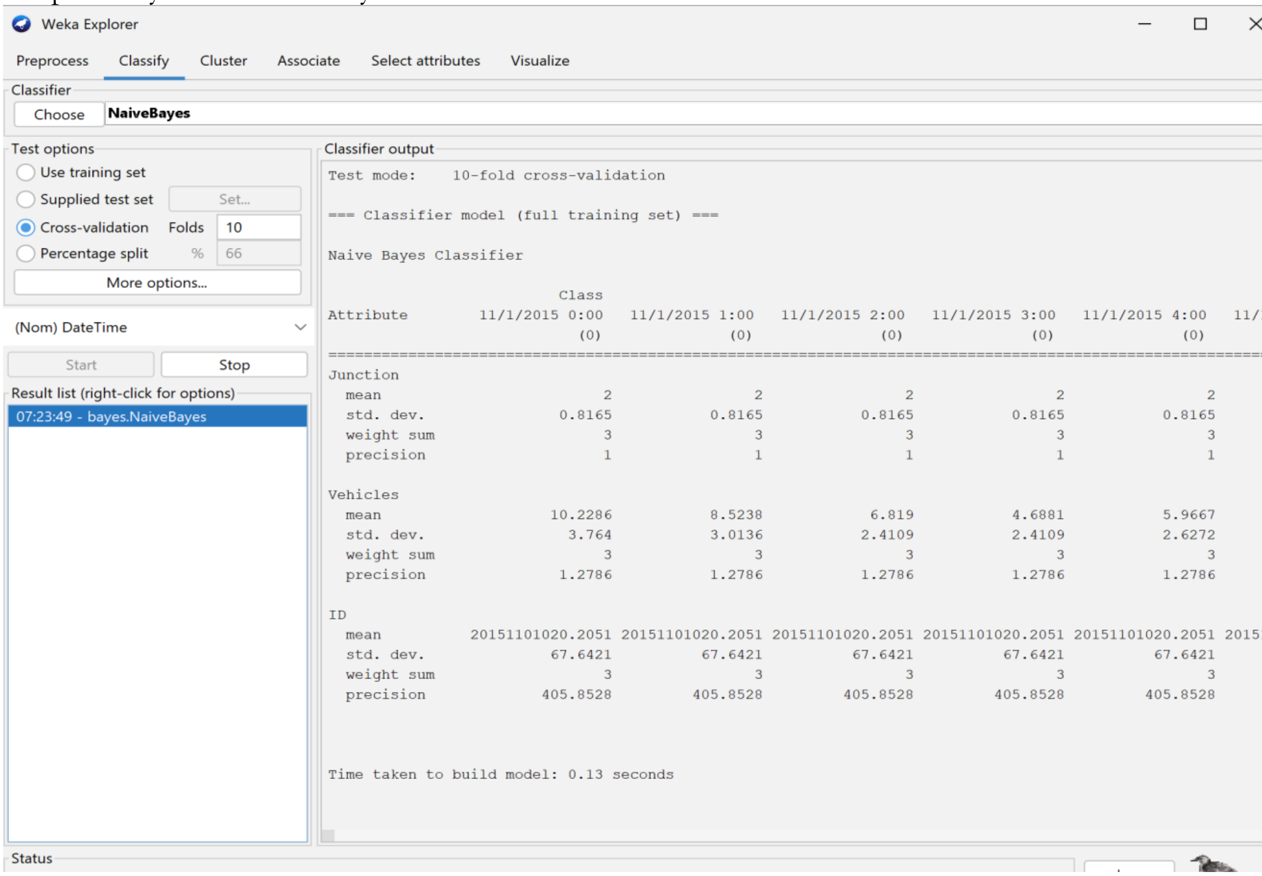

Figure 4. Naïve bays Implementation

Table 3. Naïve bays junctions, vehicles and IDs

Vehicles 0	2.18054916	22.791334	4.812000000e+4
Vehicles 1	0.96695549	20.750063	5.944887544e+6
Vehicles 2	1.00000000	9.0000000	2.01511151e+10
Vehicles 3	3.00000000	15.000000	2.01511023e+10
Vehicles 4	4.00000000	29.000000	2.01706306e+10

Support Vector Machine:

The Support Vector Machine, also known as SVM, is one of the most successful classifiers that falls into the category of being somewhat linear. It is to everyone's advantage to avoid forcing the data to fit too well. When there are fewer outliers and the data set is relatively small, SVM works quite well. Instead of attempting to fit the most significant feasible roads between two classes while simultaneously limiting margin violation, SVM may do linear and nonlinear regression, which we can refer to as support vector regression.

Table 4. SVM based junctions, and respective Vehicle IDs

Vehicle 0	0.984690	0.0988263	0.9846909
Vehicle 1	0.776699	0.0583916	0.9756431
Vehicle 2	0.787465	0.0541462	0.9874561
Vehicle 3	0.852113	0.1568756	0.7899451
Vehicle 4	0.759524	0.9998658	0.7894464

Linear Regression:

Regression is a statistical approach commonly employed in the analysis of two theories. Regression analyses are commonly employed for the purposes of forecasting and prediction, with significant overlap in their application within the field of machine learning. Furthermore, regression analysis can be employed in certain instances to establish causal relationships between independent and dependent variables. It is crucial to note that regression analysis just establishes associations between a dependent variable and a predetermined set of diverse factors.

```
epochs = 55
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/55
27/27 [==============================] - 42s 416ms/step - loss: 2.0151 - accuracy: 0.3888 - val_loss: 0.9689 - val_accuracy: 0.6619
Epoch 2/55
27/27 [==============================] - 5s 199ms/step - loss: 0.9239 - accuracy: 0.6302 - val_loss: 0.7026 - val_accuracy: 0.7714
Epoch 3/55
27/27 [==============================] - 5s 196ms/step - loss: 0.6716 - accuracy: 0.7503 - val_loss: 0.5668 - val_accuracy: 0.8048
Epoch 4/55
27/27 [==============================] - 5s 196ms/step - loss: 0.5276 - accuracy: 0.8133 - val_loss: 0.5914 - val_accuracy: 0.8333
Epoch 5/55
27/27 [==============================] - 5s 196ms/step - loss: 0.5069 - accuracy: 0.8371 - val_loss: 0.4691 - val_accuracy: 0.8429
Epoch 6/55
27/27 [==============================] - 5s 196ms/step - loss: 0.3626 - accuracy: 0.8799 - val_loss: 0.3831 - val_accuracy: 0.8952
Epoch 7/55
27/27 [==============================] - 5s 196ms/step - loss: 0.4079 - accuracy: 0.8668 - val_loss: 0.3805 - val_accuracy: 0.8571
Epoch 8/55
27/27 [==============================] - 5s 199ms/step - loss: 0.3065 - accuracy: 0.8847 - val_loss: 0.3404 - val_accuracy: 0.9048
Epoch 9/55
27/27 [==============================] - 6s 206ms/step - loss: 0.2238 - accuracy: 0.9239 - val_loss: 0.5575 - val_accuracy: 0.8429
Epoch 10/55
27/27 [==============================] - 5s 196ms/step - loss: 0.3138 - accuracy: 0.8906 - val_loss: 0.2688 - val_accuracy: 0.9048
Epoch 11/55
27/27 [==============================] - 5s 196ms/step - loss: 0.2232 - accuracy: 0.9263 - val_loss: 0.2930 - val_accuracy: 0.9000
Epoch 12/55
27/27 [==============================] - 5s 197ms/step - loss: 0.2009 - accuracy: 0.9358 - val_loss: 0.2297 - val_accuracy: 0.9095
Epoch 13/55
27/27 [==============================] - 5s 196ms/step - loss: 0.1535 - accuracy: 0.9596 - val_loss: 0.2497 - val_accuracy: 0.9238
Epoch 14/55
27/27 [==============================] - 5s 194ms/step - loss: 0.2035 - accuracy: 0.9275 - val_loss: 0.2476 - val_accuracy: 0.9286
Epoch 15/55
27/27 [==============================] - 5s 196ms/step - loss: 0.1601 - accuracy: 0.9477 - val_loss: 0.2801 - val_accuracy: 0.9286
Epoch 16/55
27/27 [==============================] - 5s 195ms/step - loss: 0.1354 - accuracy: 0.9501 - val_loss: 0.2204 - val_accuracy: 0.9333
Epoch 17/55
27/27 [==============================] - 5s 196ms/step - loss: 0.1035 - accuracy: 0.9608 - val_loss: 0.2400 - val_accuracy: 0.9524
Epoch 18/55
27/27 [==============================] - 5s 196ms/step - loss: 0.0890 - accuracy: 0.9703 - val_loss: 0.3163 - val_accuracy: 0.9048
Epoch 19/55
27/27 [==============================] - 5s 196ms/step - loss: 0.1319 - accuracy: 0.9584 - val_loss: 0.2614 - val_accuracy: 0.9429
Epoch 20/55
27/27 [==============================] - 5s 196ms/step - loss: 0.1244 - accuracy: 0.9489 - val_loss: 0.3528 - val_accuracy: 0.9190
Epoch 21/55
27/27 [==============================] - 5s 195ms/step - loss: 0.1133 - accuracy: 0.9703 - val_loss: 0.1217 - val_accuracy: 0.9524
Epoch 22/55
27/27 [==============================] - 5s 196ms/step - loss: 0.0588 - accuracy: 0.9822 - val_loss: 0.1967 - val_accuracy: 0.9429
```

Figure 5. Implementation of Linear Regression based values

KNN:

KNN is a technique for unsupervised learning that is known for its computational efficiency, particularly when dealing with big datasets. In the first step, a set of k samples is randomly selected to serve as the initial centroids, with the aim of approximating the centroids of the initial clusters. Here, k represents a positive integer value. KNN is a technique utilized for the purpose of grouping items into a predetermined number of clusters, based on their respective attributes. The process of grouping is achieved by reducing the sum of squares of distances, namely the Euclidean squared distance, between the data points and their respective cluster centroids.

```
array([1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 2, 1, 2,
       2, 4, 1, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 1, 1, 2, 2, 2, 1, 1,
       1, 1, 1, 4, 1, 1, 2, 2, 1, 1, 2, 2, 4, 1, 2, 2, 1, 4, 1, 1, 2, 4,
       2, 1, 2, 2, 2, 2, 2, 1, 1, 2, 2, 1, 2, 2, 2, 1, 1, 2, 1, 4, 4, 2,
       2, 2, 2, 2, 4, 2, 1, 2, 1, 2, 2, 2, 1, 1, 1, 2, 2, 2, 1, 1, 1, 1,
       2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 1, 1, 2, 1, 1, 1, 2, 2, 1, 1, 1, 1, 2, 2, 2, 1, 1, 2, 1, 2, 1,
       2, 2, 2, 2, 2, 4, 2, 3, 2, 2, 2, 2, 1, 1, 2, 2, 2, 1, 2, 2, 0, 1,
       0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 4, 0, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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       2, 2, 2, 2, 2, 2, 2, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0,
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       1, 2, 2, 1, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2]
     dtype=int32)
```

Figure 6. KNN values

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} * 100$$

$$Precision = \frac{TP}{TP + FP}$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

The performance evaluation was performed by employing the three main performance metrics: recall, precision, and accuracy. These are presented in tabular format in Table 2, and the manuscript also contains all of these formulations. Each of the analysis graphs for results is constructed using the performance metrics illustrated in the Figure 7 as well.

Discussion:

Transportation of both people and goods is indispensable for human existence. The substantial rise in travel time can be attributed to the increasing global population and the imperative to enhance human well-being. The rapid escalation of technological progress has contributed directly to the concurrent rise in automobile ownership. Due to the rapid increase in the number of automobiles, it is of the uttermost importance to regulate the flow of vehicles. The implementation of vehicle management systems contributes to the optimization of both voyage durations and costs. In order to implement a vehicle management system that is both efficient and effective, it is necessary to have access to accurate and comprehensive background information. For the development of an efficient vehicular management system, the collection of data regarding traffic flow is essential. The objective of this study is to provide a comprehensive overview of the most recent deep learning techniques namely SVM, Naïve Bayes, KNN, Linear Regression and Markov based employed in the field of traffic density estimations in intelligent transportation systems. Only a few of the articles published on this topic have made substantial contributions to theorizing frameworks, whereas the overwhelming majority of contributions in this field are primarily concerned with practical applications. Deep learning algorithms have proven their ability to capture the nonlinear aspects of traffic flow prediction, and these systems have exhibited encouraging outcomes. Even though there are numerous benefits associated with the use of deep learning models for the prediction of individual traffic flow, it is essential to acknowledge the existence of a number of obvious disadvantages. Academics have abandoned the use of deep learning architectures in recent years in favor of hybrid and unsupervised methods. The present study investigates the numerous deep learning architectures currently employed in the field of traffic flow prediction, as well as the increasing prevalence of hybrid methods of analysis. The weather contributes to the unpredictability of road traffic. Potential factors occur in methodologies for estimating traffic road density; for instance, air humidity and the degree to which light, heavy, or moderate precipitation affects the average speed of vehicles are significant determinants. An additional critical factor is that if the data collection is reliant on sensor data, it could potentially impact the height of the structures. This is because intelligent transportation systems typically rely on vehicles that are connected to roadside units in close proximity. It has been found that the robustness of the comparison model develops, but subsequently begins a trend that leads it to decrease until it reaches a number that is considered to be crucial. The focus of this work is on groups or ensembles. In the context of classification, an ensemble is a composite model that is made up of a number of different classifiers

The research review delves into the integration of ML and Data Mining (DM) systems within the context of sustainable smart cities, particularly emphasizing their applications in intelligent transportation systems. A considerable amount of emphasis was placed on illustrative papers that elucidate on the application of ML techniques in the context of sustainable smart city networks, particularly with regard to traffic classification. Researchers investigating the topic of anomaly traffic categorization have conducted extensive research into a variety of feature selection and extraction strategies. Utilizing the aforementioned methodologies is standard practice for enhancing the dependability and usefulness of research studies conducted in this field. In order to classify internet traffic using techniques such as machine learning and data mining, both data and data features are required. Results are shown in Figure 7 as accuracy with each attribute as well as shown in Table 2.

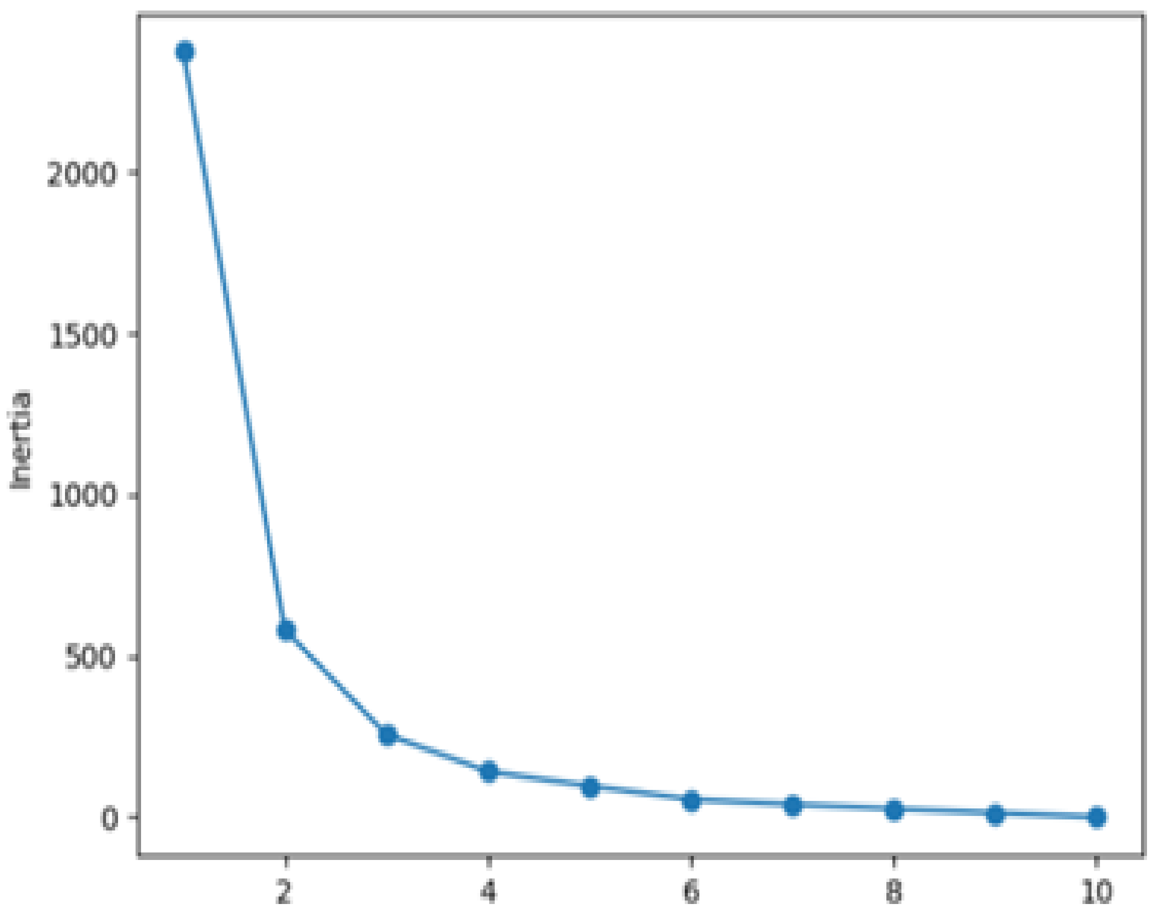

Figure 7a. KNN accuracy 67%

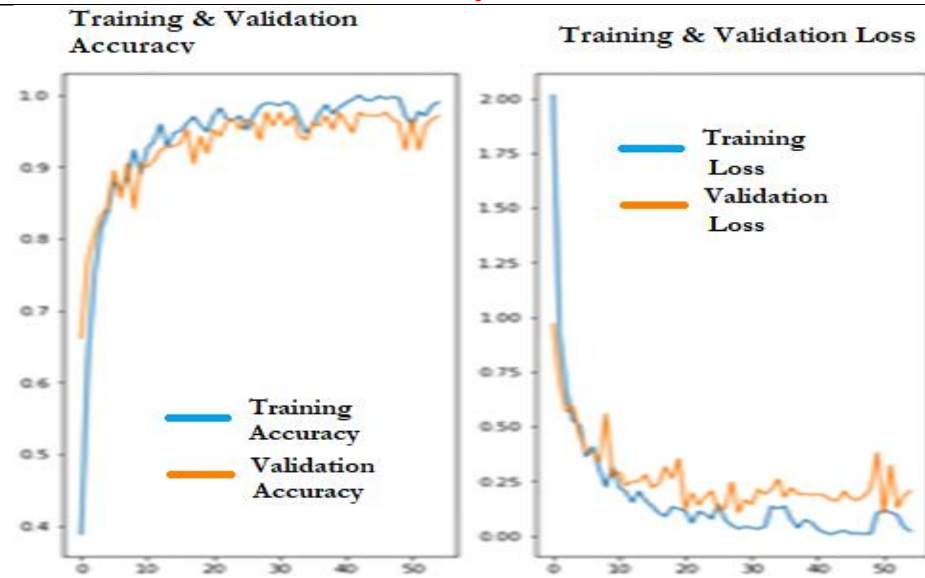

Figure 7b. Linear Regression accuracy 80%

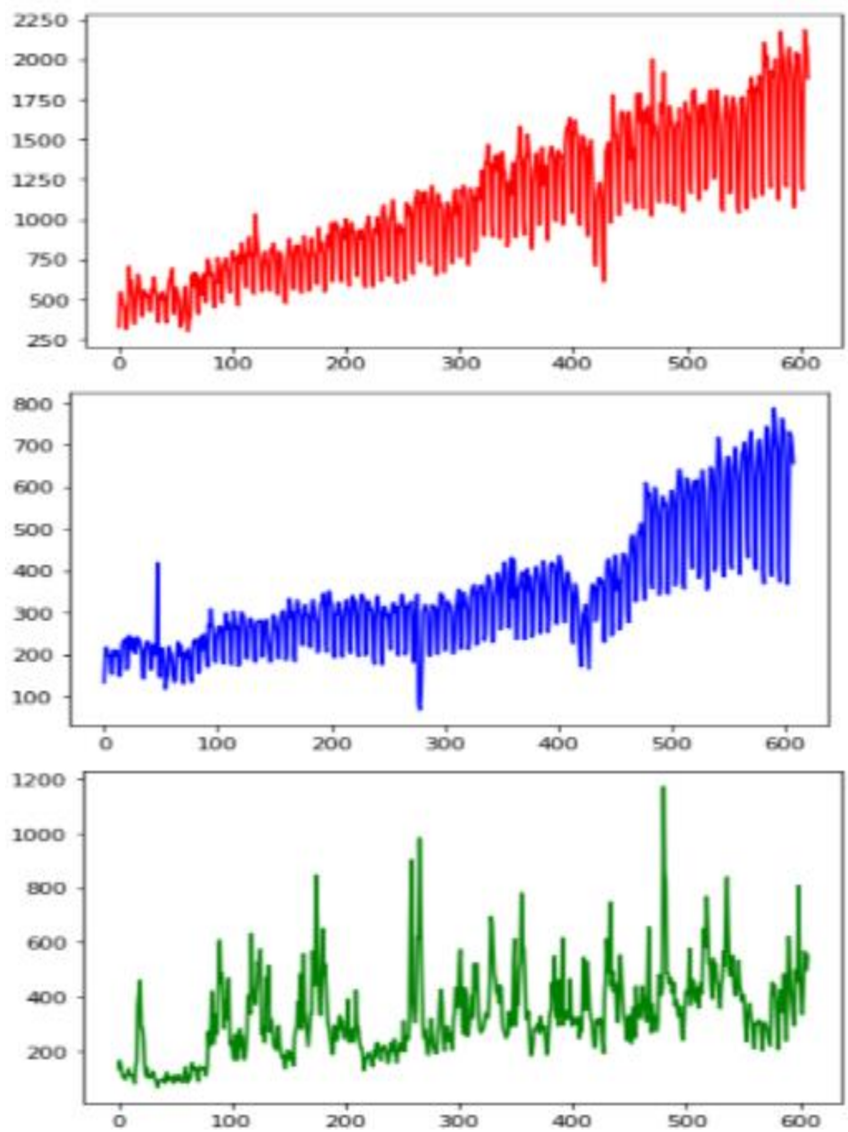

Figure 7c. SVM accuracy 56%

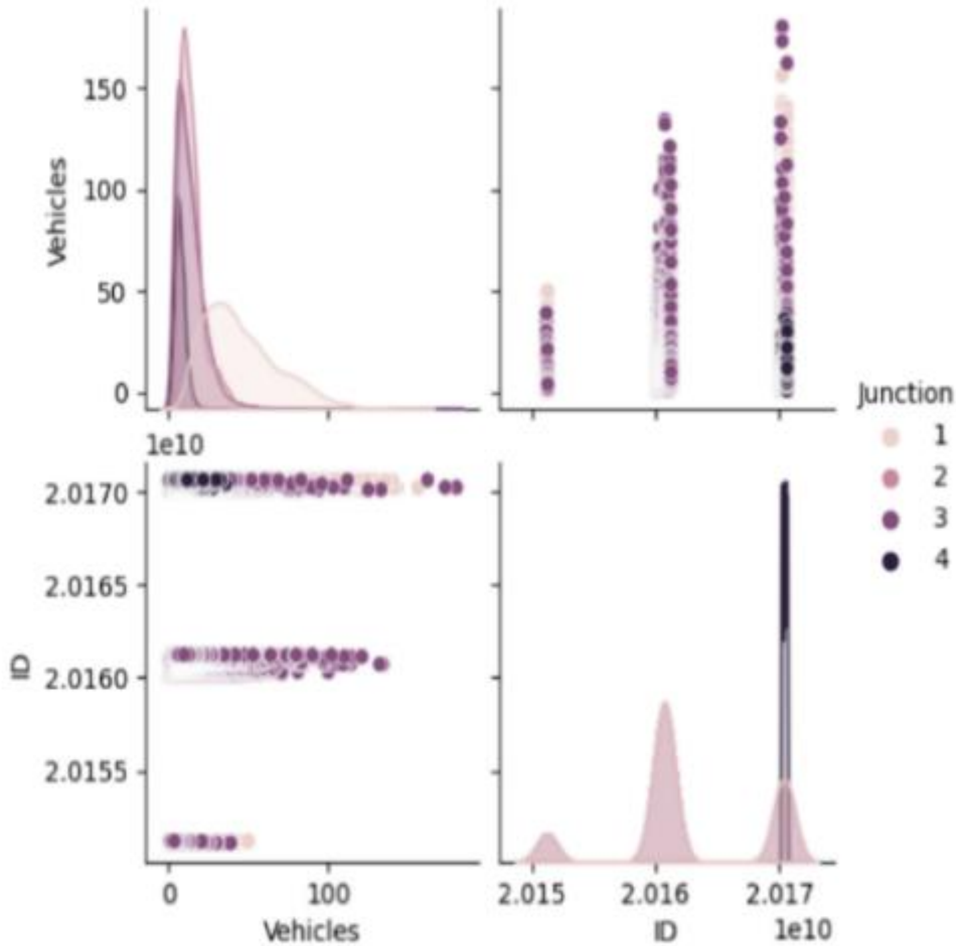

Figure 7d. Naïve Bays accuracy 92%

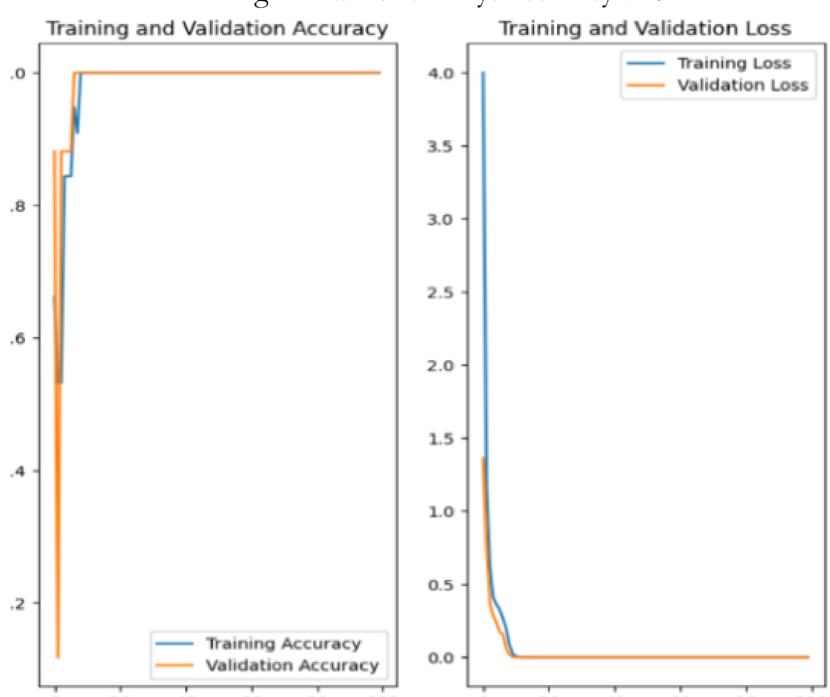

Figure 7e. Markov model accuracy 98%

Figure 7(a-e). Accuracy results of implemented algorithms.

Table 5. Implemented algorithms accuracy with respect to precision and recall

Model	Accuracy	Precision	Recall
Markov model	98%	0.982	0.943
Naïve Bays	92%	0.919	0.860
Support vector machine	56%	0.797	0.458
KNN	67%	0.921	0.837
Linear regression	80%	0.858	0.892

These assessment indicators have been extensively employed in various studies for the purpose of acquiring and assessing the outcomes. Accuracy refers to the ratio of correctly identified traffic to the total tested traffic, specifically the proportion of accurately categorized real traffic from the whole pool of tested traffic. Precision is defined as the ratio of accurately categorized traffic, specifically, the ratio of correctly identified genuine traffic to all identified traffic. Recall refers to the ratio of accurately identified traffic (f) to the total amount of traffic. It represents the proportion of correctly identified true traffic in relation to the overall true traffic. As a result, it is necessary to provide a description of well-known and frequently utilized datasets that contain specific statistical information. This paper provides a comparison of algorithms with the detailed overview of the challenges and methods used in machine learning techniques for traffic classification. These methods and suggestions pertain to the classification of traffic. In the same manner, it is essential to provide a recommendation for each method, as recommendations are also pertinent to future activities. Nonetheless, this work presents a number of traffic classification proposals that are extremely valuable for future research. This employs the two feature engineering technologies, including spatial analysis and data for specific time durations and distances from which images of particular junctions and vehicles are generated. Additionally, an additional feature engineering technology is employed to gather data through sensors. The estimation of traffic density is contingent upon the utilization of these two feature engineering technologies. Additionally, this research conducted feature engineering by incorporating domain expertise in transportation.

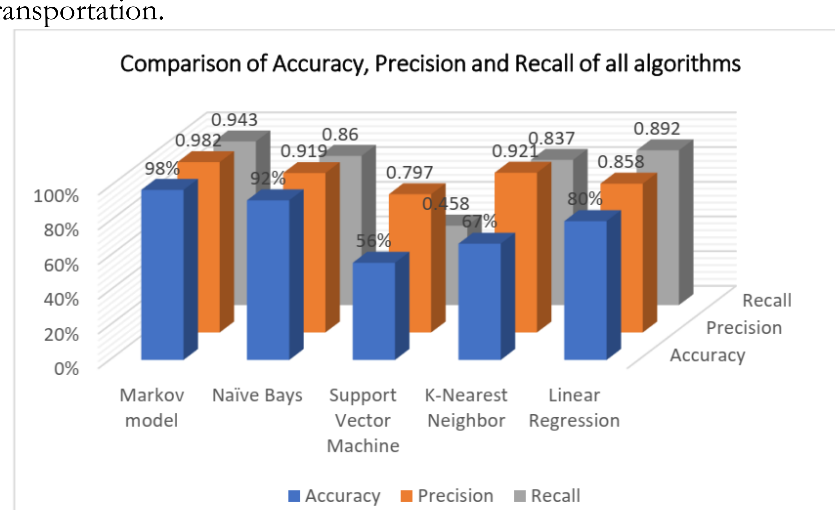

Figure 8. Comparison of average precision, accuracy, recall for all algorithms.

Conclusion:

The main objective of this study is to present a variety of classification strategies for classifying the vehicles traffic. Detailed information is provided for each classification technique. This study investigates the complexity of machine learning traffic density approaches, the extraction of features, and the application of machine learning and data mining methods. This study investigated the efficacy of six machine learning algorithms in constructing classifiers, which were evaluated on the basis of precision and accuracy. Performance of Markov based model has highest accuracy. The suggested predictive model based on best accuracy can be effectively and expeditiously employed in intelligent transportation systems. Figure 7 shows the compared results with the highest accuracy-based algorithms with respect to their values. In the context of fixed machine learning algorithms, the presented graphs illustrate the differences that can occur between the various algorithms that have been developed when the algorithms are tested with random traffic flow on random vehicles. Each algorithm possesses the capacity to handle a variable amount of random traffic load. The lack of ability of the model to adapt to road heterogeneity, such as fluctuations in car following speed, lane changing, and gap tolerance among vehicles. The method of determining the most suitable traffic model for a given environmental context is rigorous and exorbitant, because of the numerous factors that must be taken into account in future. On the other hand, it is clear from the findings that are provided in Figures 8 that the Markov-based technique has a higher degree of accuracy than the other algorithms.

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