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Empirical Research on Machine Learning Models and Feature Selection for Traffic Congestion Prediction in Smart Cities

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Abstract—The development of smart cities has occurred over the past ten years. One primary goal of "smart city" initiatives is to lessen vehicle congestion. Several innovative technologies, including vehicular communications, navigation, and traffic control, have been created by Vehicle Networking System to address this problem. The traffic data gathered by smart devices aids in the forecasting of traffic in smart cities. This project created an Intelligent Traffic Congestion Management System (ITCMS) that uses machine learning techniques and traffic data from Kaggle to decrease the amount of time spent stuck in traffic. This study aims to assess feature selection methods and machine learning models for traffic forecasting in smart cities. The feature dimension is reduced using feature selection techniques, such information gain, correlation attribute, and principal component analysis. The recommended model successfully predicted traffic flow, assisting in the alleviation of congestion. The principal component analysis with random forest model outperforms the other machine learning models and has a 95% accuracy rate.

Keywords-IoT, machine learning, feature selection, PCA, Smart city.

I. INTRODUCTION

Peer-to-peer networking and Internet Mobile were replaced by the World Wide Web and the Internet of Things (IoT), respectively, over the course of several decades. Throughout the IoT, users and things are able to connect with one another at any time, from any location, and take advantage of any available network or resource. The IoT has the potential to completely transform the way in which people interact with their surroundings and provide intelligent services that offer value in a variety of different application areas [1]. Over the course of time, the amount of data that is unusually complete has increased from one hundred forty-five zettabytes in the year 2015 to eight hundred zettabytes in the year 2023.

In addition, IoT is generating new applications while simultaneously delivering new kinds of devices. For instance, numerous modern Internet-based devices [2] are put to use, such as alarms, intelligent weather sensors, traffic lights, cameras, and meteorological stations [3]. In addition to this, it is becoming common practise to generate one-of-a-kind information for the categorization of intelligent applications, such as those used in the healthcare industry, other sectors, security breachers [4], and the transportation sector [5]. However, most of these IoT devices have limited computational capabilities [6] and are unable to deal with the information that is created on the device itself [7].

Edge computing is a workable solution because it enables fundamental systems on the system's periphery to concurrently approve the consistent processing of IoT information and offer suitable networks and computing resources [8]. However, as noted mentioned in the article [9], calculating the data insights is very difficult owing to many kinds of devices. The information related to the IoT is created because of the dynamic rotation process of the devices themselves. Due to the need that IoT access providers be used, there is a possibility that entire communication may be disrupted when there are a high number of IoT devices. Because of this, it is now abundantly evident how vital it is to anticipate various characteristics that will become available in IoT devices over time (for instance, action designs, flagship instances, etc.). In addition, the arrangement of similar devices works on the evaluation of the liabilities created and can guarantee a particular degree of service quality.

The estimation of future traffic patterns may be improved in this manner by first classifying the many IoT devices into distinct groups. In addition, the IoT access system and the edge

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computing components have the capability of providing the most precise prediction of property preconditions. This study's main findings are as follows:

- Related work is conducted to gain a better knowledge of the existing intelligent traffic prediction system.
- To identify the feasible feature selection technique for reducing the data dimension and to increase the accuracy of true positive rate.
- The pre-processed data are then trained with common machine learning models, and the results are analysed to see which models have the best performance in comparison to the others.

II. RELATED WORK

The demand for natural resources in urban areas has increased as a result of urbanisation, while a growth in pollution has also led to an increase in the negative effects on the environment. The difficulties involved in ensuring the supply of critical services become more difficult for city authorities to manage as cities continue to expand. The difficulties of setting up, implementing, and addressing urban surveillance experiments have been thoroughly analysed in a recent paper by Kumar et al. [10]. Some urban monitoring research projects encountered upon these difficulties. In this study, researchers surveyed previous research on intelligent traffic management in urban areas. It created a reference guide for future projects by first recognising the issues that were presented in the various projects. The authors have studied the challenges according to the tiers of the V-model development lifecycle.

The authors [11] have used the examples of explorer and walkers to illustrate how a method of testing that is methodical and arbitrary might lower the likelihood of prediction. The particular node that was chosen had the intention of listing replies from the correct guards. The fundamental linear regression is reliant on the information being provided and stimulates the link to the autonomous variables of location. The size of the vehicle that was registered in relation to the dependent variable and the predicted losses as a free factor; considerate the vehicle's potential attributes in the future.

Preeti and Rohit [12] have proposed stacking models based on Decision Tree, Random Forest, and XGBoost machine learning models for the Intelligent Internet of vehicles (IOVs)-based vehicles traffic prediction system for smart cities. Simulation findings show that the suggested techniques can achieve excellent prediction accuracy while keeping computational costs low. The use of ensemble learning, and the pooling of critical feature selection made this possible. When comparing the performance of two tree-based models for IOV-based traffic on a network of vehicles, the model that selected the best feature outperformed the other.

The research paper [13] have presented two unique traffic congestion detection methods: There are two algorithms for identifying traffic jams: the Traffic Congestion Detection (TCD) algorithm and the Ensemble-Based Traffic Congestion Detection (EB-TCD) method. Congestion detection via a network of sensors was the foundation for both techniques. TCD can identify congestion with just a single traffic characteristic. The TCD cleaned and pre-processed the datasets before the model evaluation. The samples' anomaly scores were then determined by computing the complete value of the first derived of each sample in the traffic feature. The anomaly likelihood of each sample was computed to determine whether it should be considered a normal or an anomalous sample. Examining the differences in the anomaly scores of the various traffic features helped to establish how much weight each one should be given. These weights indicate how much each traffic attribute contributes to explaining the behaviour of the traffic.

The computational calculation approach was used by Rembe et al. [14] to discover the linking clusters that make up the crucial measure of adaptability for various applications. By analysing the highlights of traffic photographs, exposing the expectation of streaming on the Rush Hour congestion. It simplified the traffic information with the CNN model which outperformed than other deep learning models. Tune et al. [15] Using the CNN utility to make predictions about traffic speeds and then analysing those predictions as existing expectation models. CNN focuses on providing close-ups of information; nevertheless, there is very little bang about the facts on rush hour traffic. This method calls for the use of five layers of information, among which one layer is responsible for exchanging unstable information.

HMDL, which stands for the Hybrid Multimodal Deep Learning System, was developed by Du et al. [16] pointing toward the process of predicting the flow of traffic. This model combines cadet repeat units (GRUs) and single layer CNN to complete the highlights of the link between floats and any modular transport information level. Additionally, this model identifies deep non-linear connection credits and integrates CNN with GRU dives.

Moses and Parvati wanted to construct a revolutionary model for anticipating the flow of traffic considering the components that make up the hidden pieces of information in autos [17]. This was their objective. The developer of Help Vector Relapse makes use of geographic information and non-linear planning in their work. Taking into consideration the squares of the regular mistake, the technique known as the average square error analyses the display. Increases the importance of the straight regeneration model in the process of assessing the association between scalar response and free components.

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Bang and Lee [18] either prevent inadvertent access between vehicles by coordinating the uprisings and the predicted scenario at the head of each movement, or they orchestrate the revolts themselves. If the vector-based portability expectation model is used in the TDMA-based VANET, it may help to reduce the occurrence of network outages. This model displays the versatility of public vehicles by making use of control table opening, vehicle ID, and home data of the vehicle combination trend. Information about hopping, as well as a vehicle's range and longitude.

Wei et al. [19] Concentrate on enhancing the accuracy of the prediction as the traffic continues. By utilising the Auto-encode Long Short-Term Memory (AE-LSTM) strategy, the Auto-encode process accepts the internal contract of the stream that was presented in the Gridlock. Muhammad et. al 2022 [20] have proposed an effective ML method for discovering previously hidden insights inside ITS without the need for explicit programming. This method does this by learning from data. Researchers in this paper presented a machine learning–based fusion-based intelligent traffic congestion control system (FITCCS-VN) for virtual networks.

The novelty of this work is to present a method that, makes use of a significantly reduced amount of feature. In addition, by concentrating on the combination of feature selection and machine learning model, it helps to increase the prediction accuracy of traffic in the smart cities.

III. Dataset Preprocessing

The Internet of Things smart city dataset is utilised by the framework. It is broken down into two primary stages. The first step is known as data pre-processing, and it includes activities such as the extraction of features, the standardisation of data, and the normalising of data. As a result of the large dimensionality of the dataset, the accuracy of attack detection could be hindered by the presence of some features that are either superfluous or redundant. The approach that is taken to solve this issue is known as feature selection, and it is a process in which only the pertinent subset of features from multidimensional datasets are chosen to be selected. This is done to limit the number of features that are both unneeded and noisy. In the following stage, various classifiers are educated using pertinent features to make the most accurate predictions possible regarding the flow of traffic. Performance measures such as accuracy, precision, recall, and F1-score are utilised to evaluate the machine learning models. Figure 1 illustrates the proposed methodology, which serves as a representation of the overall framework. The model was trained using five classification algorithms that are deliberated in the succeeding sub-sections.

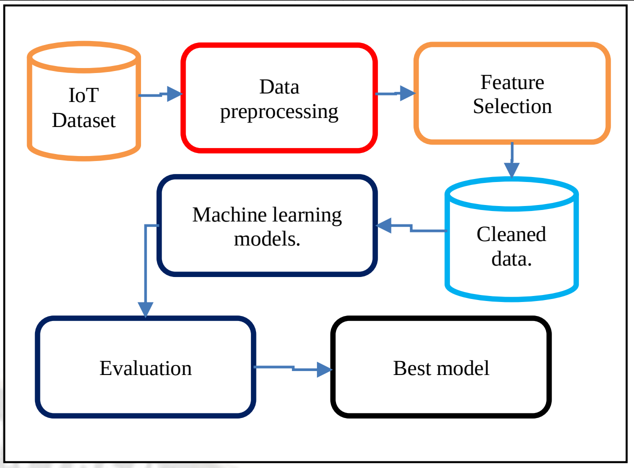

Figure 1. Research flow

A. *Data Standardisation (DS)*

The dataset consists of attributes that span a wide variety of value ranges. By using data standardisation, it changed the data so that they had a standard normal distribution instead of a normal distribution. As a result, following rescaling, an attribute's mean value equals 0 and the resultant distribution equals the standard deviation (SD). The standard score formula is stated in equation (1),

$$z = \frac{(x-\mu)}{\sigma} \qquad (1)$$

where x, σ and μ represents the sample of data, SD and mean, respectively.

B. *Data Normalisation (DN)*

To prevent the impacts of the attributes from competing with one another, data normalisation scales each continuous feature's value between 0 and 1. This experiment made use of the Python normalizer class. This class makes it possible to normalise a certain dataset.

C. *Feature Selection (FS)*

FS is a tactic used to choose trait that significantly influence and contributes to the target class in the dataset. Principal Component Analysis (PCA), IG, and Correlation Attribute Evaluation (CA) are used in this study to choose the features (PCA). To pick just individual qualified features that have substantially bigger positive or negative values. The values are closer to -1 or 1, where CA evaluates the relationship between each characteristic and the target class.

While the IG based FS approach is used to identify significant characteristics while reducing noise created by irrelevant features. These significant characteristics are derived from the entropy matrix. It is reflecting the dataset's uncertainty. PCA reduces size of huge datasets by keeping significant characteristics that rely on the target class. The FS techniques described above make it possible for training the model with features it needs to precisely forecast the labelled category.

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IV. MACHINE LEARNING MODELS

A. Random Forest (RF)

An ensemble classifier called Random Forest is employed to enhance classification outcomes. There are several Decision Trees in it. RF offers lesser classification errors as compared to other classifiers. When building distinct trees in RF, randomization is used to choose the optimal nodes for splitting.

B. Decision Tree (DT)

In the DT technique, each node represents an attribute test, each branch an outcome of that test, and each leaf node (terminal node) a label for a class. Methods for attribute selection are employed to locate nodes. These chosen properties reduce the amount of data needed in the resulting partition for tuple categorization. Consequently, those divisions representing the least amount of ambiguity or impurity. reducing the anticipated number of tests necessary for tuple categorization. The entropy class is used by ID3 algorithms to determine which features should be analysed at each node of the decision trees under consideration.

C. Logistic Regression (LR)

The probabilistic classification model of logistic regression. The issue is stated as an extended linear regression problem. Its curvature is sigmoid. The logistic or sigmoid function's equation is as follows:

$$S(X) = \frac{e^x}{1+ e^x} \qquad (2)$$

For converting values to probabilities, use this function. Real values are converted to other values between 0 and 1 to make it function.

D. K-nearest neighbours (KNN)

A value is assigned to the new data point in KNN depending on the linkage of the new data point to the training set of data points. This makes predictions using feature similarity. Calculating the Euclidean, Manhattan, or Hamming distances between a test set record and each training set record is how KNN determines the distance that exists between the two sets of data. Following that, the rows are arranged based on the value of the distance between each pair of adjacent rows. The rows that are chosen come from the K rows that come immediately before those rows. Classes are assigned to the test points in accordance with the classes that are found in those rows the most frequently.

E. Artificial Neural Network (ANN)

The ANN technique consists of three layers (i.e., input, hidden and output) of processing units that are referred to as neurons. The characteristics of the dataset, in addition to the classes that need to be uncovered and selected through the application of a wide variety of neural techniques. It decides the amounts of neurons that are actually present in each of the above mentioned layers. To compute the weighted sum of the connections that are created between neurons, the ANN technique makes use of a wide number of different activation functions in a variety of different combinations. This method adjusts the biases in both the second layer and third layer while the model is being trained and tested. These adjustments take place in both layers. This contributes to a reduction in the amount of errors that occur and contributes to an improvement in the results' correctness.

V. RESULTS AND DISCUSSIONS

A. Evaluation Metrics

For evaluating the relative efficacy of different machine learning algorithms, a confusion matrix is utilised as a tool. The values of “True Negative” (TN), “True Positive” (TP), “False Negative” (FN), and “False Positive” (FP) are combined in this matrix for generating a variety of measures. The following is a list of the performance measures that are utilised in the process of evaluating models through the utilisation of the confusion matrix.

Accuracy is a measure of how well or closely a model's estimated value corresponds to its real or actual value, which corresponds to the proportion of all samples that are properly categorised. Accuracy is a measure of how well or closely a model's estimated value corresponds to its real or actual value. The accuracy of the model may be calculated with the help of the following formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} (3)$$

Precision elucidates the percentage of relevant occurrences within the selected examples that are in fact affirmative. Applying the formula shown below will help you determine accuracy:

$$Precision = \frac{TP}{TP+FP} \qquad (4).$$

Recall, also known as the true positive rate, is the metric that is used to calculate the proportion of true positives that are correctly identified (TPR). For the calculation of recall, the following equation is utilised:

$$Recall = \frac{TP}{TP+FN} (5)$$

The F1-score is the harmonic mean of precision and recall. To determine an individual's F1 score, the following formula is utilised:

$$F - Score = \frac{Precision*Recall}{Precision+Recall} (6)$$

B. Analysis

The experimentation of the suggested SCTS (smart city traffic system) method is carried out using the dataset that is accessible to the public [21]. The information was made public as part of a competition hosted on Kaggle for developing an

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efficient smart city. The ability of the government to accurately forecast traffic patterns and meet the needs of the public with respect to transportation is one of its most pressing challenges. There are a total of 48,121 train records and 11,809 test records included in the dataset. The produced dataset is then divided into training and test sets with appropriate proportions of 80% and 20%.

Performance evaluation of featureless categorization models: Figure 2 provides a summary of the results of classification models that did not include feature selection. RF had the greatest values for accuracy, precision, recall, and F1-score, respectively, within this table, with references to 89.39%, 76.19%, 72.16%, and 74.2%, respectively. The scores that LR received for accuracy, precision, recall, and F1-score were the lowest. On the other hand, DT received the highest scores possible: accuracy of 88.39%, precision of 70.15%, recall of 72.17%, and F1-score of 71.14%. The lowest values were found for LR's accuracy, precision, recall, and F1-score. LR and KNN both claimed to have the same level of accuracy, despite the fact that LR's precision, recall, and F1-score values were higher than those of KNN. Despite the fact that ANN demonstrated an average level of performance, with values for accuracy, precision, recall, and F1-score that were approximately 84.90%, 61.10%, 53.12%, and 54.15%, respectively.

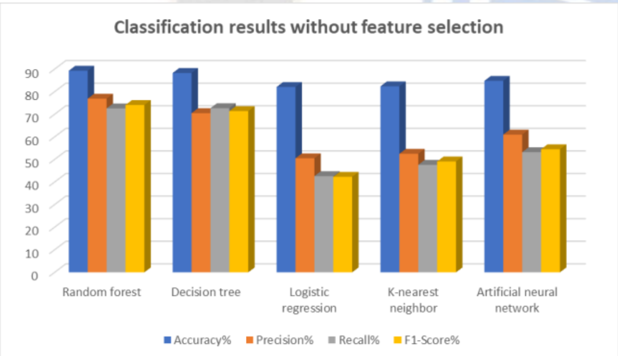

Figure 2. Classification results without feature selection

Evaluation of the effectiveness of feature-based classification models: CA, IG, and PCA are the three feature selection approaches that are used in this investigation. The results of the training of the classifiers utilising the characteristics may be seen in Figure 3.

It was revealed that the RF classifier had the highest level of accuracy (about 89.15%) when the IG approach was utilised. The RF classifier had a precision rate of 76.18%, a recall rate of 72.13%, and an F1-score of 73.17%. Additionally, it had the highest F1-score. LR and KNN, in contrast to other classifiers, had trouble with IG since both their recall and F1-score values were lower than 50%. This was the case for the IG and KNN classifiers. There is not much of a difference in the accuracy of RF and DT classifiers because when utilising the IG approach, both produce nearly identical values for accuracy, recall, and F1-score. This is one reason why there is not much of a difference in the accuracy of RF and DT classifiers. The only significant difference is that DT was only able to achieve an accuracy rate of 69.16%, while RF was successful in accomplishing 76.18% of its target.

It has been noticed that the accuracy of the classifier suffers in general whenever the model is trained by employing the correlation attribute method. The random forest classifier managed to attain the best level of accuracy (86.13%) despite having poor precision, recall, and F1-score metrics, which was also the case. There is just a small difference, ranging from 2% to 5% in either direction, between the accuracy of decision tree and ANN classifiers and that of RF classifiers. This difference is negligible. On the other hand, the ANN classifier possesses performance characteristics that are not nearly on par with those of the random forest and decision tree classifiers. The logistic regression and KNN models, both of which have performance characteristics that are lower than average, are the models that provide the lowest level of accuracy.

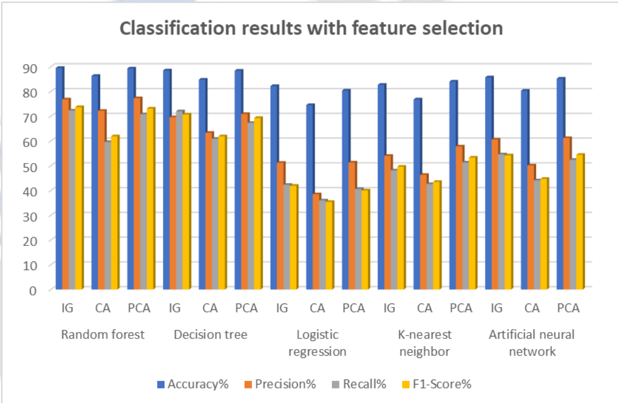

Figure 3. Classification results with feature selection

It was discovered that the RF classifier had the highest rates of accuracy (89.13%), precision (87.13%), recall (80.18%), and F1-score (83.11%). This was discovered via the use of the PCA feature selection methodology. Even though they all had performance ratings that were lower than the IG feature selection approach, all of the classifiers had accuracy rates that ranged from 80% to 89%. The F1 score and recall rate for LR were both the lowest possible, with 40.6 percentage.

After conducting research that compared the effectiveness of three distinct approaches to feature selection, it was found that the feature selection strategies utilised by information gain and principal componentanalysis performed significantly better than those utilised by correlation attribute. This was the conclusion reached as a result of the analysis. When trained with information gain and principal component analysis, the random forest and decision tree classifiers reached an accuracy level that was comparable to one another. The accuracy was between 88% and 89% at this point in time. On the other hand, the outcomes that these classifiers exhibited were around average in terms of metrics like accuracy, recall, and F1-score. Since classifiers had around the same level of accuracy before the feature selection process, it is safe to believe that the data have not undergone any substantial transformations as a result of the application of the feature selection procedures.

VI. CONCLUSION

This paper presents an empirical study on the various machine learning models to develop an intelligent traffic control system. The framework that has been suggested makes use of a variety of pre-processing methods, which include strategies for data standardisation, normalisation, and feature selection. As a result, in order to construct an efficient machine learning model, we made use of an innovative combination of various pre-processing strategies. On the traffic dataset that was made public by Kaggle, the effectiveness of several feature selection strategies such as information gain, principal component analysis, and correlation attribute was analysed and evaluated. The applicability of the selected characteristics, in addition to the utilisation of data standardisation and normalisation approaches, is analysed by putting them on five distinct classification models. According to the findings, the characteristics chosen by principal component analysis contributed significantly more to improving accuracy than any of the other methods. Based on the findings of the evaluation, it is possible to draw the conclusion that both the random forest and decision tree classifiers performed admirably over the dataset regarding the evaluation metrics. In this study, the RF model attains 90% of accuracy with PCA. The work can be further improved by experimenting using nature inspired optimization technique for selecting appropriate features.

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