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Deep Learning on Traffic Prediction Methods, Analysis and Future Directions

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ABSTRACT

Accurate traffic forecasting is essential for intelligent transportation frameworks. Course arranging, vehicle dispatch, and facilitating gridlock may all profit from precise traffic anticipating. This challenge is difficult due to the complex and dynamic spatiotemporal relationships that exist between various segments of the road network. This topic has recently received a lot of research attention, particularly the deep learning method, which has significantly improved traffic forecasting abilities. This work expects to introduce a far- reaching assessment of traffic prediction strategies in view of deep gaining according to different points of view. To get things started, we'll summarize and classify the current methods for traffic forecasting. Second, we discuss the most recent approaches utilized in various applications for traffic prediction. Thirdly, to help different specialists, we gather and organize generally utilized public datasets from the ongoing writing. In addition, we conduct extensive investigations to evaluate the displayof various methodologies on a genuine public dataset in order to provide an evaluation and examination. Inconclusion, we examine irritating issues in this area.

KEYWORDS – *Traffic Prediction, Deep Learning, Spatial Temporal Dependency Modeling.*

I. INTRODUCTION

A brilliant city is gradually taking the place of the cutting-edge city. The rapid rate of population growthand urbanization puts a serious strain on traffic across the board in metropolitan areas. The Intelligent Transportation System (ITS), which is an essential component of successful urban communities, includes traffic anticipation as one of its fundamental components. Precise traffic gauging is essential for some genuine applications. Traffic stream expectation, for example, may assist urban communities with eliminating clog; Estimates of vehicle hailing request can inspire vehicle sharing organizations to pre-assign vehicles to regions with popularity. We can look at this topic from different perspectives now that more information about traffic is available.

The literature on traffic prediction in specific circumstances has been examined from a variety of perspectives in a few recent studies. [2] looked at methods and applications from 2004 to 2013 and compiled a list of 10 major issues at the time. Transient traffic estimating is the essential concentration, and the pertinent writing is generally founded on traditional methodologies. A third report, named "Short-Term Traffic Prediction," presented the traffic expectation techniques and proposed a few thoughts for future exploration. [4] gave sources to social occasion traffic information and principally focused on customary ML methods. The meaning of traffic estimation and potential areas for further investigation were discussed in [5]-[7] listed significant models considering conventional methods and early deep learning techniques. Alexander and co. [8] took a gander at deep neural networks for anticipating traffic. Three notable deep neural architectures were discussed: feedforward neural network, convolutional neural network, and recurrent neural network. Nonetheless, [8] did exclude various late turns of events, for example, diagram based deep learning. An outline of the design of chart based deep learning with various traffic applications is given in [An overview on the utilization of deep learning models in rush hour gridlock information examination was introduced by 10]. However, it only looks at the forecast for traffic flow. It is advantageous to examine all traffic prediction jobs together because they generally share similarities. Subsequently, there is as yet shortage of enormous and exhaustive studies on traffic gauge overall.

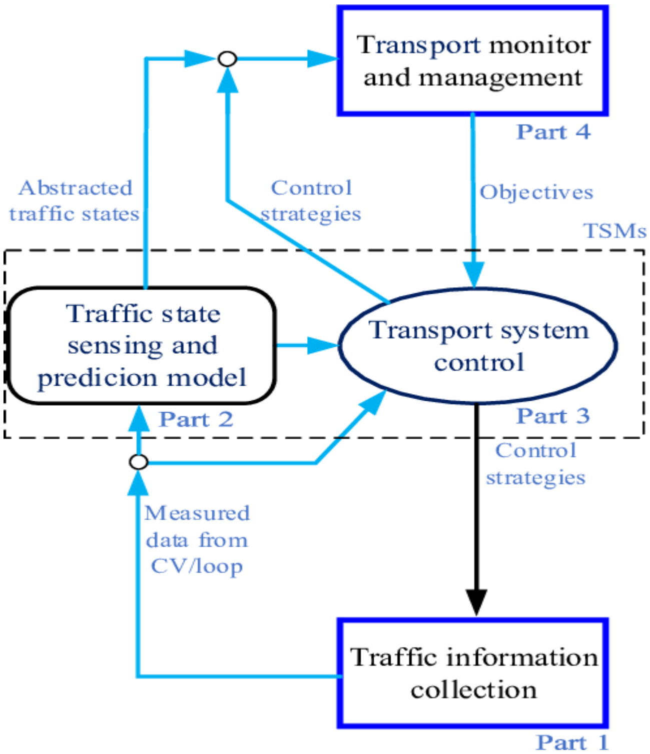

Fig.1: Example figure

II. LITERATURE REVIEW

DNN-based prediction model for spatio-temporal data:

The accessibility of spatio-temporal (ST) information with unmistakable spatial (like topographical pecking order and distance) and worldly (like closeness, period, and pattern) highlights has expanded because of headways in area procurement and remote correspondence innovation. This article (DeepST) offers a profound learning- based expectation model for spatial and worldly information. The engineering of DeepST iscomprised of two sections, the two of which arebased on top of ST space information: worldwide and spatiotemporal. A convolutional neural network architecture is used in the spatio- temporal component to simulate temporal proximity, period, and trend in addition to spatial near and distant relationships. The worldwide part is planned to catch worldwide components like work days and endsof the week. We created UrbanFlow1, an ongoing group stream guaging framework, utilizing DeepST. DeepST's capacity to catch the spatiotemporal highlights of ST information has been affirmed by explore results on an assortment of ST datasets, showing its benefits more than four standard methodologies.

Short-term traffic forecasting: Where we are and where we're going

Since the mid-1980s, momentary traffic estimating has been a fundamental part of most of ITS examination and applications; most of work has been placed into creating techniques that can be utilized to foresee traffic conditions and model traffic qualities. Various examinations have utilized single-point roadway information and univariate numerical models to gauge traffic volumes or travel times. The accessible writing is broad. Scholastics currently have an unrivaled chance to expand points of view and drive concentrate on in ten testing yet generally neglected fields thanks to the far-re a c h i ng utilization of complex PCs and numerical models and late mechanical progressions. This study examines current issues and suggests ways to tackle them in the future.

A brief overview of machine learning methods for short-term traffic forecasting and future directions

Assessing transient traffic is a key piece of wise transportation systems. A ton of headway has been made in this space as of late because of the fast improvement of ML calculations and the remarkable accessibility of information. In this review, we need to give a concise outline of ML calculations for momentary traffic determining to help related research. The limitations of traffic forecasting are first discussed, followed by several approaches to modeling interdependence across time and space. In conclusion, we present a number of significant future research areas.

Survey on traffic prediction in smart cities

The accommodation and viability of our process are improved by intelligent transportation, for example, intelligent traffic signals. It is currently conceivable to gather spatiotemporal information and afterward utilize this information to accomplish the objective of insightful transportation with the advancement of portable Web and area innovations. Traffic forecast assumes a urgent part in such manner. In this review, wepresent an extensive outline of traffic expectation from the spatiotemporal information layer to the wise transportation application layer. To begin, we confined the whole survey scope into four fragments, which are, all together, spatiotemporal data, preprocessing, traffic estimate, and traffic application. We will audit past work on the four segments from here on out. At first, we partition traffic information into five classifications in light of contrasts in overall setting. Second, we focus on four significant strategies for planning information: information cleaning, It can more readily fit non-direct angles in rush hour gridlock information, has less imperatives on forecast assignments, and requires less earlier information about the association between traffic designs. There are various sub-classes of the ML approach, for example, the relapse model and the piece-based model,among others. Picking a satisfactory ML model is the most important phase in fostering an expectation framework for any of these models. To achieve this, we require a strong understanding of the different ML techniques; We take a gander at something other than the exactness of various models; we like wise take a gander at the right circumstance and, at times, the sort of issue the model was made to settle. Subsequently, the objective of this exploration is to inspect the qualities and shortcomings of various ML models while likewise giving an unmistakable and far-reaching examination of everyone. Different ML models will be arranged according to the ML hypothesis they use in order to accomplish this. We will first provide a brief outline of the ML hypothesis that is utilized in each classification before zeroing in on the specific modifications that are made to the model when it is applied to various forecast situations. Meanwhile, we'll contrast one or two classifications with find out about which ML approaches are best at which sorts of expectation undertakings in view of their singular model properties. In addition, wedraw attention to the significant add-ons utilized in traffic prediction and theoutstanding issues in the traffic prediction industry.

III. METHODOLOGY

Alexander and others proposed a traffic prediction study using deep neural networks. It discussed three notable deep neural structures: repetitive brain organization, feedforward brain organization, and convolutional brain organization. Notwithstanding, diagram based deep learning and other ongoing leap forwards were avoided regarding the conversation. a glance at the design of chart based profound advancing and the way things are utilized in rush h our gridlock overall. A review about utilizing profound learning models to dissect traffic information was distributed by the creators. Be that as it may, it just ganders at the gauge for traffic flow. It is advantageous to examine all traffic prediction jobs together because they generally share similarities. Subsequently, there is as yet a shortage of enormous and exhaustive studies on traffic gauge overall.

Disadvantages:

1. A comprehensive and methodical evaluation oftraffic forecasts as a whole is still lacking.
2. Route planning, vehicle dispatching, and traffic congestion may all benefit from accurate traffic forecasting. This challenge is difficult due to the complex and dynamic spatiotemporal relationships that exist between various segments of the road network.

This work means to introduce a thorough assessment of traffic forecast strategies in light of deep learning according to various viewpoints. To kick things off, we'll sum up and group the ongoing techniques for traffic guaging. Second, we discuss the most recent approaches utilized in various applications for traffic prediction. Thirdly, to help different specialists, we gather and organize normally utilized public datasets from the ongoing writing. Furthermore, to give an assessment and investigation, we direct broad trials to assess the presentation of different methodologies on a genuine public dataset. To wrap things up, we checkout at annoying issues in this area.

Advantages:

1. Participants who wish to quickly investigate traffic forecasting in order to identify relevant subfields will find this paper useful.
2. Moreover, it is an astounding reference and request asset for scholastics working in this field, which might help with relevant exploration.

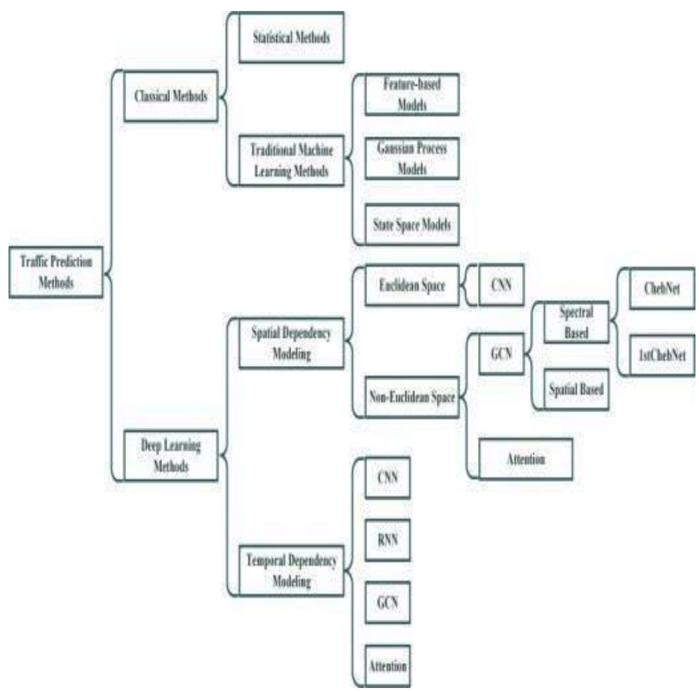

Fig.2: System architecture

MODULES:

To complete the previous project, wesupported the modules listed below.

Examining the information: Information will be entered into the framework using this module.

- The relationship: We will review handling-relevant information using this module.
- Separation of information into training and testing: The information will be divided into training and test using this module.
- Creation of models: Make models of GMAN, STGCN, STSGCN, ASTGCN, CNN, CNN+RNN, DCRNN, SVM, Random Forest, Decision Tree, MLP, and Voting classifier.
- Login and registration for users: By using this module, you can register and log in.
- User feedback: Prediction input will be provided by using this module.
- Prognosis: The predicted final value will be presented.

IV. IMPLEMENTATION OF ALGORITHMS:

In the context of Deep Learning on Traffic Prediction Methods Analysis and Future Directions, Random Forest can be used as a complementary model to deep learning techniques. Here's a brief overview of how Random Forest may be incorporated into the project.

Hybrid Modeling Approach:
Integrating Random Forest with deep learning models creates a hybrid approach. Deep learning models (e.g., neural networks) are powerful but may lack interpretability and can be prone to over fitting, especially with limited data. Random Forest, being an ensemble of decision trees, can provide robustness, handle on-linear relationships, and offer interpretability.Feature Importance and Selection:
Random Forest can be employed to assess feature importance in the traffic prediction context. This helps in identifying which features contribute significantly to the prediction task, aiding in feature selection for the deep learning models.

Handling Heterogeneous Data:
Traffic prediction often involves diverse data sources such as weather, time of day, and historical traffic patterns.
Random Forest is adept at handling heterogeneous data, making it suitable for combining various features in the prediction process.

Resilience to Noise and Outliers:

Random Forest is known for its resilience to noisy data and outliers, providing stability to the overall prediction model. This can be particularly beneficial in real-world traffic scenarios where unexpected events or outliers may occur. Ensuring Robust Predictions. The ensemble nature of Random Forest, aggregatingpredictions from multiple trees, contributes to a more robust overall prediction, potentially reducing the impact of errors or uncertainties. Model Interpretability: The ability to interpret and understand the reasoning behind predictions is crucial in traffic prediction systems. Random Forest's simplicity and transparency make it easier to interpret compared to some complex deep learning models. In the context of Deep Learning for Traffic Prediction, decision trees may not be the primary method used, as deep learning models like recurrent neural networks (RNNs) or Long Short-Term Memory networks (LSTMs) are more commonly employed due to theirability to capture temporal dependencies in sequential data. However, decision trees could be used as part of a hybrid approach or feature engineering process in the following ways:

Feature Selection: Decision trees can help identify important features for traffic prediction. By analyzing thedecision tree structure, relevant features impacting traffic patterns can be identified and incorporated into the deep learning model. Preprocessing: Decision trees can assist in preprocessing data by handling missing values or encoding categorical variables. This cleaned data can then be fed into the deep learning models for traffic prediction. Ensemble Methods: Decision trees can be combined into ensemble methods like Random Forests. The ensemble model may enhance the predictive power, and the output from such models can be integrated into the overall trafficprediction system.

MLP: Multilayer perceptron (MLP) is a completely connected type of feedforward counterfeit brain network. The term "MLP" can refer to either any feedforward ANN or networks with many layers of perceptron's (with limit initiation), both of which are questionable. Mention phrasing. When there is only one secret layer available, multi-facet perceptron's are frequently referred to as "vanilla" brain organizations.
Support Vector Machine :Feature Extraction: Extract relevant features from traffic data, such as traffic volume, time of day, weather conditions, etc.

Data Preprocessing: Prepare the dataset for training by normalizing, scaling, and cleaning the data.
Integration with Deep Learning Model: Combinethe SVM with a deep learning model, such as a neural network, to create a hybrid model. This hybrid approach leverages the strength of SVM in handling complex decision boundaries.

Training the Model: Train the combined model on historical traffic data, allowing the deep learning component to capture intricate patterns while theSVM focuses on optimizing decision boundaries.

Evaluation and Fine-Tuning: Assess the model's performance using metrics like accuracy, precision, recall, and F1 score. Fine-tune the parameters ofboth the SVM and the deep learning model for optimal results.

Ensemble Techniques: Explore ensemble techniques where predictions from SVM and the deep learning model are combined to achieve a more robust and accurate traffic prediction.

Future Directions: Investigate advancements in SVM and deep learning techniques for traffic prediction. Consider incorporating real-time data, exploring different neural network architectures, andoptimizing hyper parameters.

Model Diversity: Various deep learning models, each designed to capture different aspects of traffic patterns, are trained independently. These could include recurrent neural networks (RNNs), convolutional neural networks (CNNs), and other architectures tailored for time series data.

Individual Model Training: Each model is trained on historical traffic data to learn patterns, dependencies, and trends. The diversity in model architectures ensures a comprehensive understanding of the complex traffic dynamics.

Voting Classifier Configuration: A voting classifier is then configured to aggregate predictions from the individual models. Common types of voting include hard voting (majority vote) and soft voting (weighted average of probabilities). The idea is that the ensemble decision is more reliable than that of any individual model.

Ensemble Decision: When new traffic data is presented for prediction, each individual model generates its prediction, and the voting classifier combines these predictions to make a final decision on the expected traffic conditions. This helps mitigate theweaknesses of individual models and enhances overall prediction accuracy.

Model Evaluation and Tuning: The ensemble model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Hyper parameter tuning may be performed to optimize the ensemble's performance.

Future Directions: The project may explore advanced techniques like model stacking, where predictions from individual models are used as input features for another model. Additionally, attention mechanisms, transfer learning, or the integration of external factors (weather, events) could be considered to further enhance traffic prediction accuracy and robustness.

Convolutional Neural Network(CNN) ;

Data Input: Traffic data, such as images from surveillance cameras, satellite imagery, or sensor readings, serves as input to the CNN.

Feature Extraction: CNNs excel at learning hierarchical features. In this case, they automatically extract relevant spatial features from the input data, such as patterns in traffic flow,congestion, or anomalies.

Temporal Aspects: CNNs might be combined with recurrent layers or other temporal modeling techniques to capture the temporal dynamics of traffic patterns. This helps in understanding how traffic conditions change over time.

Prediction: The trained CNN is used for predictingfuture traffic conditions based on the learned spatial and temporal features. This could include forecasting congestion, estimating traffic flow, or predicting potential incidents.

Performance Evaluation: The accuracy of the predictions made by the CNN is evaluated against real-world traffic data. Metrics such as Mean Squared Error (MSE) or Mean Absolute Error (MAE) may be used to assess the model's performance.

Future Directions: The analysis of different CNN architectures, hyper parameter tuning, and experimenting with additional data sources or modalities can be explored to enhance prediction accuracy.

Integration with other deep learning models or ensemble techniques for a more comprehensive approach to traffic prediction.

Incorporation of real-time data and adapting the model for dynamic traffic conditions. ExploringInterpretability methods to understand the learned features and improve model transparency.

Traffic Conditions and Car Count:

- Normal Traffic: This has the least number of cars on the road, represented by the shortest bar on the left. During normal traffic, the flow of vehicles is smooth and steady, with minimal congestion.
- Moving Traffic: The bar representing moving traffic is slightly taller than the one for normal traffic. This indicates a moderate increase in the number of cars on the road. While there's still movement, it may be slower than during normal traffic conditions.
- Busy Traffic: This is depicted by a taller bar compared to moving traffic. Busy traffic signifies a significant risein the number of cars, leading to slower speeds and potentially some congestion.
- Heavy Traffic: The tallest bar on the right represents heavy traffic. This is when the road is at or near its maximum capacity, resulting in slow-moving or even completely stopped vehicles.
- Understanding the Distribution: The graph displays a left-skewed distribution, meaning most data points are concentrated towards the normal traffic with fewer instances of heavier traffic conditions. This reflects the typical scenario where most of the time, traffic is lightto moderate, with occasional periods of heaviercongestion.

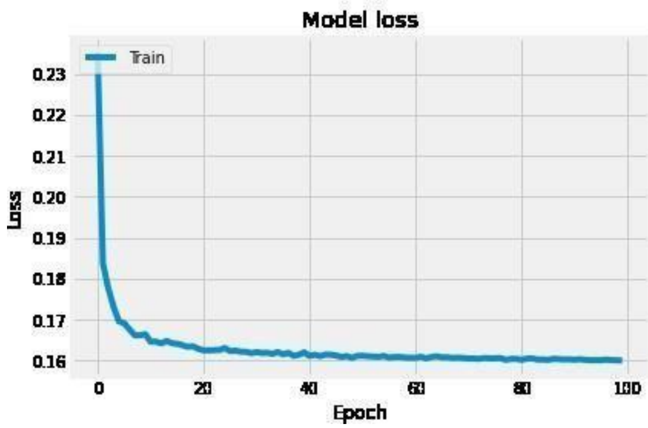

Fig.3.1: Model loss

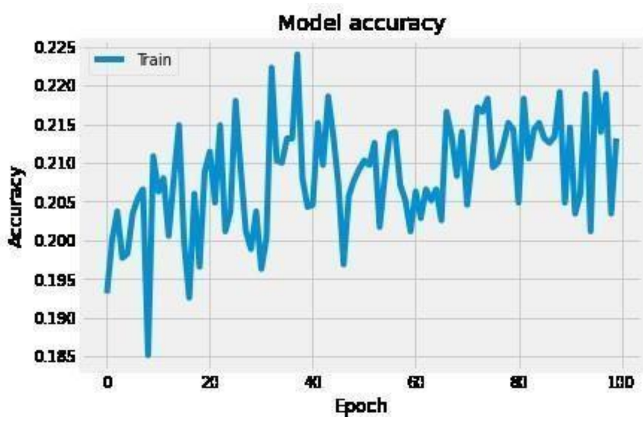

Fig.3.2: Model Accuracy

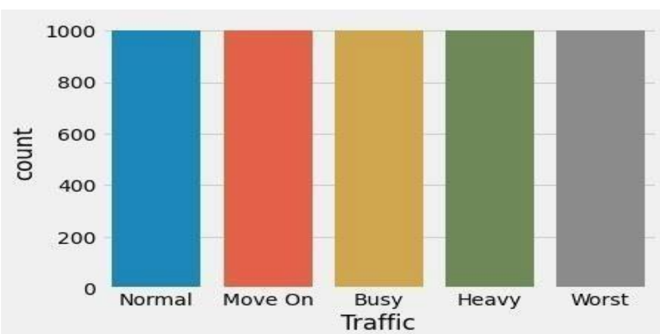

Fig.3.2 : Count Plot

Additional Factors:

It's important to remember that this is just a general representation. The actual number of cars on the road under each traffic condition can vary depending on several factors, such as:

- Time of day: Traffic tends to be heavier duringrush hours and commutes.
- Day of the week: Weekends and holidays oftensee increased traffic compared to weekdays.
- Weather conditions: Rain, snow, or other adverse weather can significantly impact trafficflow.
- Accidents or road closures: These can cause sudden and unexpected congestion.

By considering these factors along with the graph, you can get a better understanding of how traffic conditions might play out on a specific road at a particular time.

This information elaborates on the image and provides you with a clearer picture of traffic distribution based on different conditions.

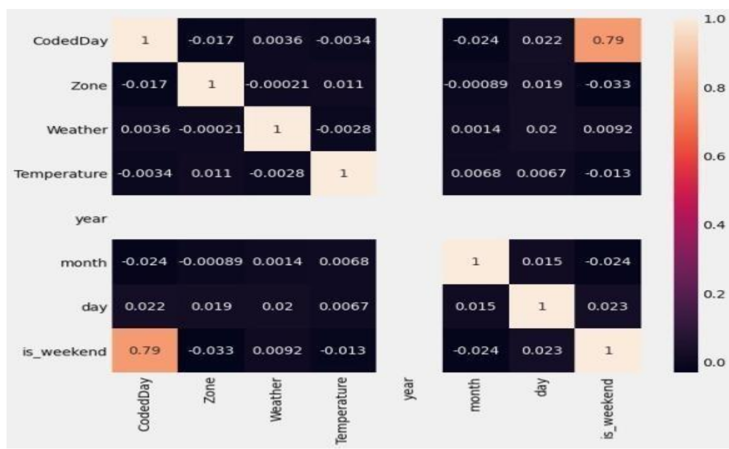

Fig.3.4: Basic Visualization

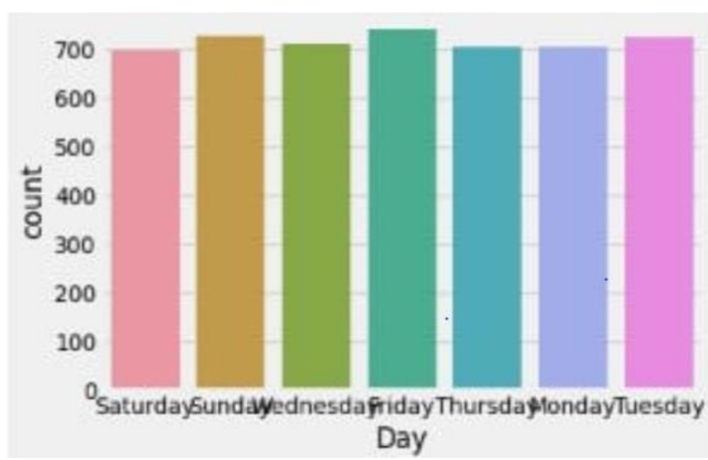

Fig 3.5 A week’s analysis

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