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Intelligent Traffic Management Using Big Data Analytics and IOT

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Abstract: With rapid growth in personal luxury and increasing jobs, People are comfortable using their personal vehicles rather than public transport to fulfill their transportation needs. This is because of ease of access and feasibility to use the vehicles at their own will at any point of time. It is leading to heavy traffic congestions and long waiting periods at traffic signals which is becoming a heavy burden in all major cities and will be affecting environment because of pollution caused by so many vehicles and also will disturb the individual's time schedule. This paper proposes a system using data analytics, machine learning algorithms, Internet of things to predict the traffic flow, generate precise data about real time traffic congestions at that instant and rerouting the vehicles using navigation through a less congested path ultimately developing an Intelligent Traffic Management system. The architecture of the system is based on image analysis of vehicles using cameras at signals, using GPS in mobiles to monitor traffic in particular route. The combination of these two can be used to generate useful data about traffic congestions. Next part is calculating the efficient path to reach the destination with the generated data to minimize traffic and reach destination short period of time. The generated efficient route and traffic intensity is updated to the user with the help of maps application.
Keywords: data analytics, machine learning, GPS, image analysis, intelligent traffic management system, Internet of things

I. INTRODUCTION

The primary contributor to the issue of "Traffic Congestion" is the usage of personal automobiles for commuting rather than public transportation. There can be a variety of personal reasons why individuals are unable to use public transportation. However, this issue cannot be resolved just by encouraging individuals to utilize public transportation rather than using their own automobiles. We devised an intelligent solution to this issue using new developments in machine learning and several algorithms for data analysis. With the fast advancement of communication and sensing technologies, low-cost and effective sensors, greater data storage and retrieval efficiency, and low-cost storage of huge data, it is simple to extract, utilize data for our convenience. The present traffic control system employs a pre-programmed time interval mechanism for traffic-signal changes. This system can be changed using data analytics and machine learning. The primary problem in Data Analytics is gathering relevant and useable data in order to design a solution. Continuously updated data must be uploaded to the data model, and the prediction techniques generated by algorithms must be capable of delivering correct reports from this ever-growing data.

The primary data source for this model is crowdsourced data. Nowadays, with the advancement of technology in the vehicle sector, a GPS sensor is being employed in the vehicle for smart applications. GPS data collected from autos may be quite beneficial in developing the data model. The GPS sensor (global positioning system) determines the vehicle's precise location. With the position of all vehicles, it is possible to anticipate whether there is traffic congestion or not. This data is especially valuable for determining the traffic rate or density of traffic at a certain place. The traffic density can be estimated by comparing the relative positions of a given car to the number of cars present within a metered radius of that place. The vehicle's speed also has a significant impact in this. Another source of helpful data is the CCTV cameras installed on the routes.

Image analysis techniques can be used to estimate the number of automobiles on the route. OpenCV is a collection of computer vision-related functions geared primarily at real-time computer vision. This can be used for real time video analysis to calculate number of vehicles that are being crossed. Eventually we can calculate traffic rate using the time for a vehicle to cross the marked point. We can also calculate traffic density by counting the number of automobiles present in the space compared with the speed of the automobile.

One of the great components of the proposed design has been formalised in a platform prototype that is based specifically on **Kafka**, a useful tool for processing Big Data streams efficiently. Owing Kafka's built-in systems, the records evaluation is scalable, that is, it can handle a large number of records sources concurrently sending records at excessive rates, and it is dependable, in the sense that it can withstand hardware failures without loss of records.

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II. BACKGROUND

A. Characteristics of Intelligent Traffic Management System

The main objective of this research is to use Kafka, one of the most popular Big Data techniques, to develop an extendable real-time traffic management system. As a result, it's critical to investigate certain resemblance and differences between the existing control system and stream analytics of Kafka. The analysis of the circumstance (data collection) and putting the specified control plan into action are the two basic components of real-time traffic control systems (information distribution and data processing). A local system examines input data in real time, which is then combined and processed to determine the scenario (example: incident detection). When a certain threshold is reached, the controller objective function is optimized using one of the established techniques. In certain instances, the strategic goal is defined by a central system. Local systems, on the other hand, are adaptable enough to behave in a variety of ways in response to changing circumstances. Nearly all prevalent traffic control techniques are the model predictive control (MPC) and feedback loop. They are, however, mostly single-objective and need data that has been purposefully perceived (i.e., basic traffic flow parameters).

B. Big Data Analytics

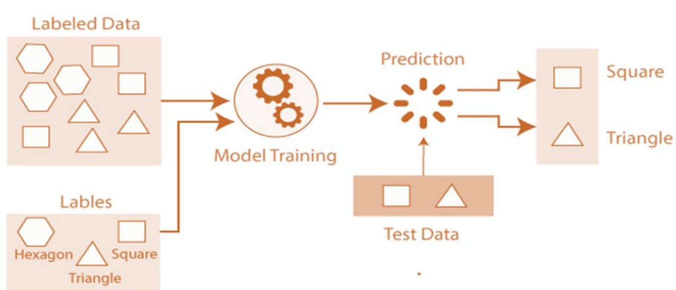
By using a collection of storage and processing units dubbed clusters, Big Data analytics techniques scale in terms of the volume and speed of data that has to be examined. This overcomes the limits of a single CPU and the disk usage of a single hard drive but adds difficulty to the process of configuring and running the relevant tools. The core premise of Big Data analytics is "bringing computation to data": each computer in a Big Data cluster functions on its own set of local data storage (map function); Individual machine findings are then combined and summarized (reduce function). Various Big Data analytics solutions have emerged to meet the needs of a wide range of applications and users. The primary contrast is in between tools that do what are known as batch analytics on history of data, which is stored usually in a NoSQL database (e.g., Cassandra, HBase) or a Hadoop Distributed File System (HDFS). Spark, Tez, and Hadoop's MapReduce, as well as different SQL-like front ends similar to pig and Hive, are all examples of batch analytics technologies. On the other hand, there are tools that use stream analytics, that is, those that analyses data as it arrives in preset time frames. This is ideal when data-driven choices must be made quickly. Flink, Kafka Streams (a Kafka extension), and Spark Streaming are all noteworthy technologies in this area.

III. BIG DATA ANALYTICS METHODS

Machine learning allows the extraction of patterns and models from enormous amounts of data, so it is the most extensively utilized modelling and analytics tool in Big Data ecosystems. Machine learning hypothesis has also been widely utilized in ITS sectors to undertake data analytics. Depending on the extent to which the data set is full and available for study, machine learning algorithms can be categorized as supervised, unsupervised, or reinforcement learning techniques. With the fast growth of Artificial Intelligence in the last few years, strong deep learning models is used to ITS.

A. Supervised Learning

Supervised learning is a subfield of machine learning in which computers are taught using well-labeled data and then forecast the outcome based on that information. Data that has been labelled implies that some of the input data has already been marked with the expected output. The training data supplied to the machines functions as a supervisor in supervised learning, teaching the machines on how to effectively predict the output. It works on the same concept as when a student is learning under the supervision of a teacher. The act of providing the machine learning model with both suitable input and output data is known as supervised learning. The goal of a supervised learning algorithm is to find a mapping function that connects the input variable (x) to the output variable (y).



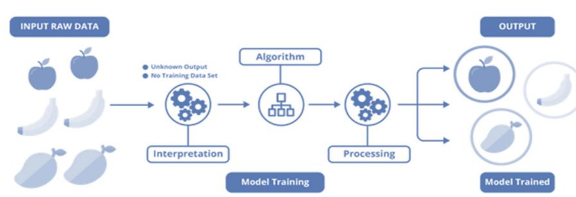


Fig 1: Unsupervised Learning

Fig 2: Supervised Learning

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B. Unsupervised Learning

The trained data for some pattern recognition tasks contains a collection of input vectors x with no target values that match. The aim of unsupervised learning tasks like these could be to find clusters of similar events in data which is known as clustering, or determining the data distribution in space, which is described as density estimation. In another way, with an n-sample space x1 to x n, no genuine class labels are supplied for every sample, resulting in what is referred to as "learning without a teacher".

1) Unsupervised Learning Issues

a) Unsupervised Learning activities are more difficult than Supervised Learning activities.
b) How can we know whether the findings are meaningful in the absence of response labels?
c) Allow a professional to examine the findings (external evaluation)
d) Define a clustering objective function (internal evaluation)

2) Unsupervised Learning is Classified into two Categories

a) *Parametric Unsupervised Learning*: In cases like this, we suppose that the data are distributed parametrically. It is predicated on the assumption that particular data sample originate from a probability-distributed population defined by a predefined parameters set. In theory, every member of a normal group of distribution has the similar form and is calculated by the mean & standard deviations. That is, if you are aware of the standard deviations and mean of the distribution and presume that it is usual, you can calculate the possibilities of any upcoming observation. It includes the building of Gaussian's Mixture Model and the use of the Expectation Maximization method to forecast the sample's class. This instance is far more difficult than conventional supervised learning since there is no response label and in consequence no proper measures of correctness to validate the outcome.
b) *Non-parametric Unsupervised Learning*: In this non-parametric type of unsupervised learning, the data is clustered, and each cluster (ideally) contains information about the categorization and classes represented in data. Here it is a frequently used technique for modelling and analysing data using small selected sizes. Non - parametric models, unlike parametric models, do not require the use of a modeller to draw any predictions regarding the distribution of the population and As a result, they're often described as a "distribution-free" approach.

C. Deep Learning

Deep learning models outperform typical machine learning models. They've been used around a bunch of areas in Intelligent Traffic Management systems. Deep learning models have become a significant method for predicting traffic flow density in the domain of traffic flow. Deep learning models make use of a broader range of system features and a more complicated design than typical Artificial Neural Networks, and so can outperform typical machine learning model. They've been extensively implemented in ITS systems. For instance, using GPS data from taxis, a deep Recurrent Neural-Network design and Restricted Boltzmann Machine is used to simulate and forecast the growth of traffic congestion. With the use of Big Data, defect diagnosis on bogies is carried out using deep neural networks. The input is made up of data received from all highways. Taking into account the link between traffic flow with period, data from earlier intervals of time, i.e, $\chi t-1, \chi t-2, \ldots, \chi t-l$, are utilised to forecast flow of traffic at specified interval of time t. The proposed model intrinsically takes into consideration of the traffic flow correlations on a geographical and temporal scale.

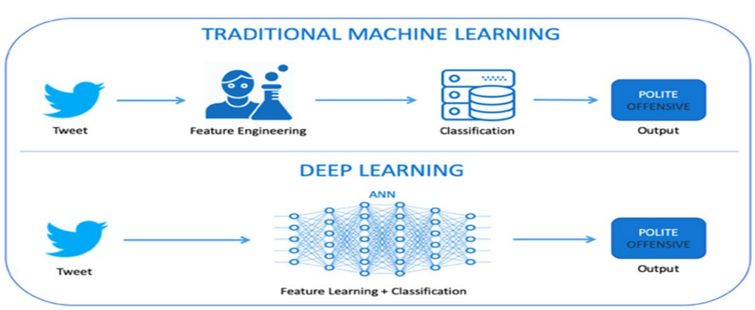

Fig 3: Machine Learning

IV. BIG DATA COLLECTION SOURCES

A. Big Data From GPS

GPS is the most widely used method of tracking one's whereabouts. With GPS position monitoring, traffic data may be obtained more effectively and securely. By combining geographic information systems (GIS) or other map-display technologies, GPS offers a potential tool for data collecting, and the acquired data may be utilised to solve a variety of traffic challenges, including travel mode recognition, trip delay assessment, and traffic monitoring.

B. CCTV Image Processing

Many communities now have affordable video surveillance systems, commonly called closed-circuit television (CCTV). They have seen remarkable expansion in recent years and often comprise a variety of cameras with varying resolutions, mounting points, and frame rates. CCTV operates 24 hours a day, seven days a week, and creates vast amounts of data, dubbed Big Data. Among other things, this data may be used to provide the groundwork for an automated traffic monitoring system.

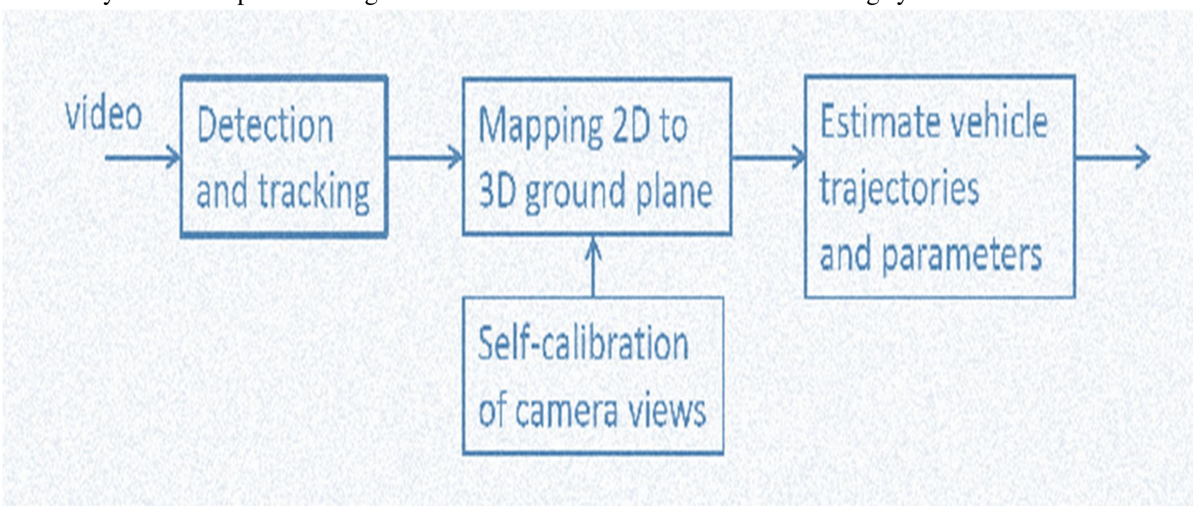

Fig 4: Image processing

This system consists mainly of two blocks:

1) *Object Detection:* As of now, the majority of object detectors are based on convolutional neural networks (CNN) and fall into one of two categories: single-stage detectors and two-stage detectors. Single-stage detectors are often quick and can predict the bounding boxes of objects as well as classes in a single network run. YOLO [5] and SSD [4] are two well-known single-stage detectors. These designs perform especially well when the target items take up a significant portion of the picture. The famous UA-DETRAC vehicle detection dataset is an example of this kind of data [7]. Dmitriy Anisimov and Tatiana Khanova [1] demonstrated with this data that a properly developed SSD-like detector can operate at speeds more than 40 frames per second on a current CPU while retaining acceptable accuracy. Another example of a good speed-precision trade-off is the YOLO v2 architecture [30], which was optimised for vehicle recognition via the use of anchoring clustering, extra loss normalisation, and a multi-layer feature fusion method.
2) *Multi-object tracking:* Due to the advancements in the accuracy of the object detectors stated before, the tracking-by-detection paradigm has become the de facto standard for multi-object tracking (MOT) tasks. Tracking is defined as a data association (DA) issue in this paradigm, with the goal of combining fuzzy detections over numerous frames into extended tracklets. Traditionally, tracking-by-detection approaches depend only on motion information from the detector and address the DA issue using optimization approaches. Multiple Hypothesis Tracking (MHT) [3] and Joint Probalistic Data Association Filter (JPDAF) [6] are well-known examples. Although these algorithms address the association issue frame by frame, their combinatorial complexity grows exponentially with the number of monitored objects, rendering them unsuitable for real-time tracking. On the other hand, a recent SORT tracker [2] shown that a basic Hungarian algorithm with Kalman filtering for movement predictions may attain real-time processing speed while preserving acceptable performance.

C. Data collected Through Sensors

Sensors deployed in ITS captures data regarding statistics on traffic speed, traffic volumes, and road network, amongst other things, may be found in. On-road sensors (e.g., infrared and microwave detectors) have evolved to collect, calculate, and transmit traffic data [8]. As described in [8], sensor data gathering may be classified into three categories: roadside data, floating automobile data, and broad area data [9]. The term "roadway data" refers mostly to data gathered by sensors situated along the roadside. For many years, conventional roadside sensors such as inductive magnetic loops, pneumatic road tubes, piezoelectric loop arrays, and microwave radars were employed. With recent advancements in technology, next generation roadside sensors including as ultrasonic and acoustic sensor systems, magnetic vehicle detectors, infrared systems, light detection and ranging (LIDAR), and video image processing and detection systems are progressively becoming available. Floating car data (FCD) primarily refers to vehicle mobility data collected at various places within an ITS system using specific detectors implanted in cars [10]. Certain onboard sensors give reliable and efficient data for route selection and estimate. Popular FCD sensor technologies include automated vehicle identification (AVI), licence plate recognition (LPR), and transponders such as probing cars and electronic toll tags. Wide area data refers to traffic flow data acquired over a large area using a variety of sensor monitoring methods, including photogrammetric processing, sound recording, video processing, and space-based radar. Sensors are being introduced in the car sector at the moment to monitor each and every aspect of the vehicle. The route is evaluated, and things are detected using 3D Mapper. This is used to identify obstacles in self-driving automobiles. The technique is used with machine learning to enhance item recognition and classification based on their form and motion. This data from the car may be communicated through IoT, which may be quite beneficial in terms of supplying big data for the analytics of intelligent traffic management system.

D. Open-Source Data from Various Transport Modes

With the increase in use of cab services like Uber and Lyft by the customers, this data of automobiles and traffic routes that are being used by the application can be used to feed the data model and predict traffic which can provide better results while predicting the traffic. The data from such apps can be reliable and can be accurate as the drivers follow the path that is being shown in the app and the data will be updated from time to time. From this we can obtain real time changing data in the city or the real time updates in the traffic. This data can also be used to train models as some of the data will be recurring daily as some may be preferring to travel via cabs daily for their work.

V. ARCHITECTURE

Travel speed prediction has been one of the most difficult issues to address. Individual data sources, such as CCTV cameras and traffic sensor data, have traditionally been used by controllers to feed regression or time-series forecasting models. These methods don't take use of the vast amount and diversity of transportation data that can be analyzed using contemporary data, engineering, and machine learning tools. cutting-edge deep learning can be utilized to create speedy, high-performance speed forecasts for the road network under typical operating circumstances by ingesting and integrating enormous volumes of diverse data. When the road network is not running normally, the most intriguing situations to investigate are often present. If there is a special event, construction on the road, or a traffic incident. Due to a paucity of training data, AI models have traditionally struggled with occasional non-recurring occurrences like these. Several methods for generating high-quality forecasts in certain circumstances, including using classic traffic simulation to analyze crucial non-recurrent occurrences can be implemented. The simulation may run many scenarios and compare the results for travelers using pre-configured reaction strategies.

The data analytics engine analyses and/or controls the logic established by each customer, which might range from a basic feedback loop to complex machine-learning algorithms. Additionally, customers may select the time intervals for getting the analytics engine's output. As data is received, it is handled using user-defined reducer functions. These functions are topic specific. For instance, in the case of speed data, a suitable reducer function may calculate the incoming data's moving average. A separate evaluator function is run at the conclusion of each time period. The evaluator has access to the outputs of all reducers; here is where judgments may be made based on the combined analysis of the various reducers. In the case of automated traffic control, the evaluator activates modifications to the traffic system on a conditional basis through the change provider.

Deep learning algorithm is implemented in the prediction model based on the algorithm described in . *Essien [11]* . The proposed framework is composed of an eight-layer bidirectional LSTM stacked autoencoder. The Rectified Linear Unit (ReLU) was employed as the activation function for all interconnected layers (excluding the output layer), which injected non-linearity into the learning process. Deep learning network performance is highly reliant on important parameters that must be established via a process called hyperparameter optimization or hyper-parameterization. To determine the ideal set of hyperparameters for this investigation, we used a grid search methodology.

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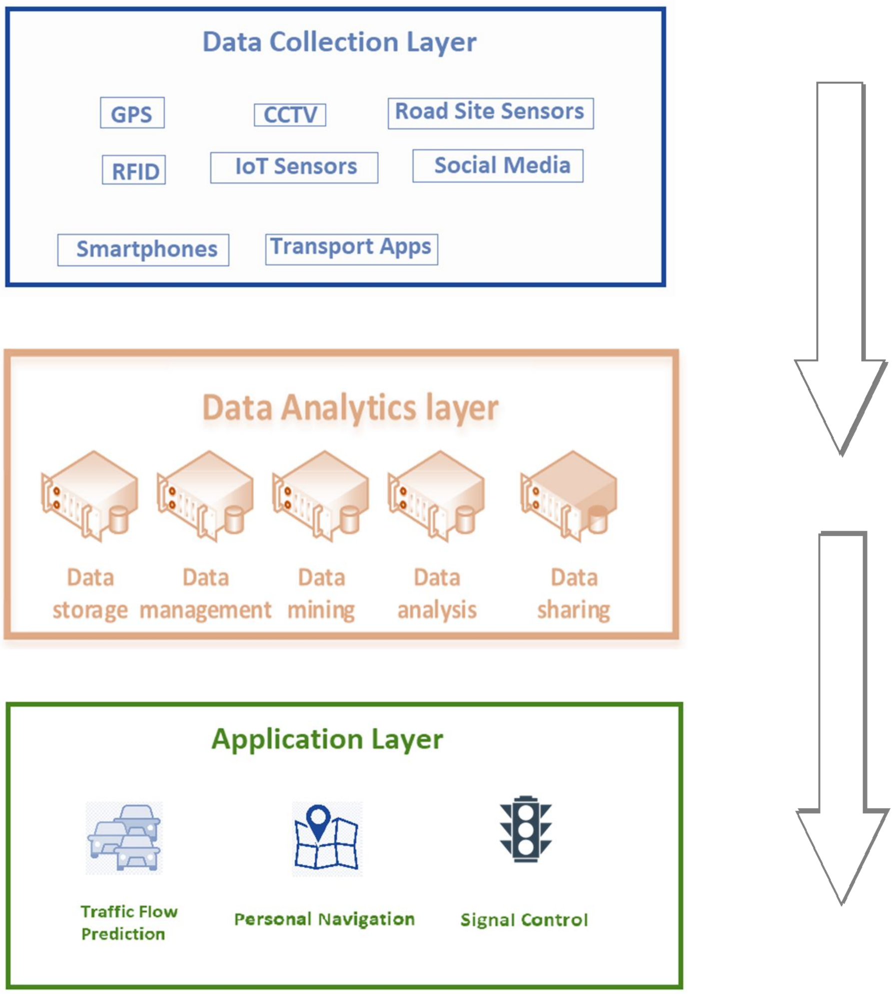

Fig 5: Control Flow

The algorithm consists of the following steps to evaluate:

1) Input: Gathered sequence of data of a particular area
2) Output: Predicted traffic flow of a particular road of the area

a) Divide the real-world data obtained into 70:30 ratios for training and testing.
b) Select a look back step size of b in the training data, and at time t, create lookback observations as $x_1, x_2, x_3, \ldots$
c) x_b as the input and x_b+1 as the expected value y_t
d) Establish a random initialization procedure for model parameters, weight w_t and bias c.
e) Train the model using a forward greedy-layer wise approach and update the model parameters using bi-directional processing.
f) The back propagation algorithm optimizer is used to update the model.
g) Loss function minimization
h) Utilize test data for model validation and another batch of training data for a subsequent retraining procedure.
i) Rep until the training set is completed.
j) Return the output sequence of the prediction Y.

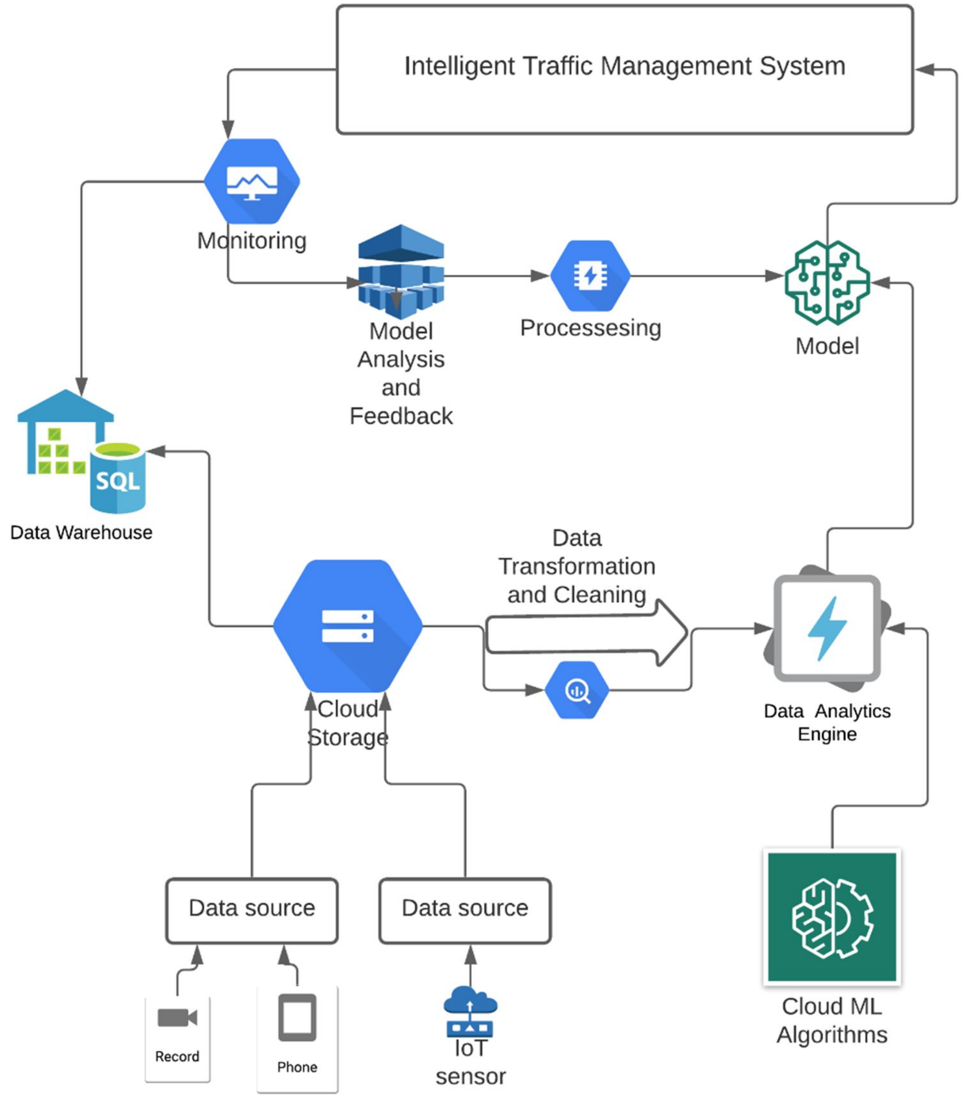

Fig 6: Architecture of Intelligent Traffic Management System

VI. CHALLENGES

A. Data Privacy

The most perplexing and concerning problem in the age of Big Data is privacy. There is a chance of compromising the personal data during the data imports and transfer, collection, and use. Historically, data acquired from transportation networks were non-personal in nature, such as car location and traffic flow data. Nevertheless, there was major increase in concerns regarding personal privacy as many public and commercial companies are collecting personal data without the consent of user. For instance, the locations of persons and transport vehicles can readily be gathered. If this data is not securely safeguarded, those who hijacks the data can do significant things to that particular person. Therefore, it is very important to secure and safeguard the information that has been gathered from different resources. To avoid such unlawful exposure of personal private information, the government should implement certain comprehensive privacy rules stating which data can be collected by the organizations that will not affect the user, the breadth of data publication and use, the fundamental principles of data distribution, and data accessibility, among other things. Transport agencies should heavily supervise the definition of personal data, tighten their administration of data security services, and use extensively complex algorithms to increase the level of data security which can help develop these kinds of applications in an easier manner.

B. Processing Power

For Big Data framework in Intelligent Traffic Management System, timeliness is critical; such heavy framework include pre-processing of the real-time traffic data, calculation the state of traffic, controlling the traffic in real time, dynamic route guiding, and real time scheduling of public transport. The data which is acquired in variety of forms from a variety of sources must be compared to historical data and then processed quickly. The data processing system must be capable of handling more complex and growing data. How to ensure process accuracy with so gigantic and rapid data is a major concern in this application. Numerous general-purpose Big Data frameworks that support real-time data sources have emerged recently, including Matillion, Spark, Snowflake and Kafka Streams. This can help predicting the average speed of moving traffic and jammed areas of a particular route. These frameworks offer effective solutions for real-time data processing. To deploy these services in cloud platform for real time monitoring and feedback requires a lot of processing power, storage, and stable internet connection to transfer bulk data files across different platforms for storage and processing.

C. Power Usage

A continuous monitoring system must be created to always collect data. This can ensure that the forecast is correct and that the model is updated on any accidents or occurrences that may affect the model's assessment. High power is required to keep the systems operational to co-operate with the usage of this application by the users. The cost required to keep such systems in cool environment cannot be neglected.

VII. CONCLUSION

We presented a complete and adaptable architecture for solving real-time traffic management with the help of Big Data techniques and deep learning. The architecture is the result of a methodical examination of the domain's needs. Real time deep learning algorithms simultaneously combined with kafka streaming or spark streaming services for the data flow can lead to development of highly optimized model for prediction of the traffic. The study's primary weakness was a lack of access to real-world data. By training the model using real-world data, we can significantly increase the model's efficiency. Data collection is a significant constraint. Maintaining such massive volumes of data requires a great deal of work and management mechanisms.

Despite its simplicity, this real-world example necessitates the analysis of vast and diverse data imports from various sources. Despite the fact using such a framework to execute solely standard control measures necessitates a significant amount of work, such frameworks are critical for emerging autonomous vehicles, particularly for maintain the control measures between each constituent concurrently, such as premeditated decisions for individual vehicle drive. With the advancement of autonomous vehicle technology, the model may be very beneficial in assisting a car in predicting traffic flow and redirecting to another route. Thus, more research may be conducted to combine this technology with driverless autos and other vehicles in order to intelligently route users to their destinations with minimal traffic interruptions. Another area to investigate is the use of IoT in the construction of smart cities, which may significantly aid in the gathering of real-world data for the model.

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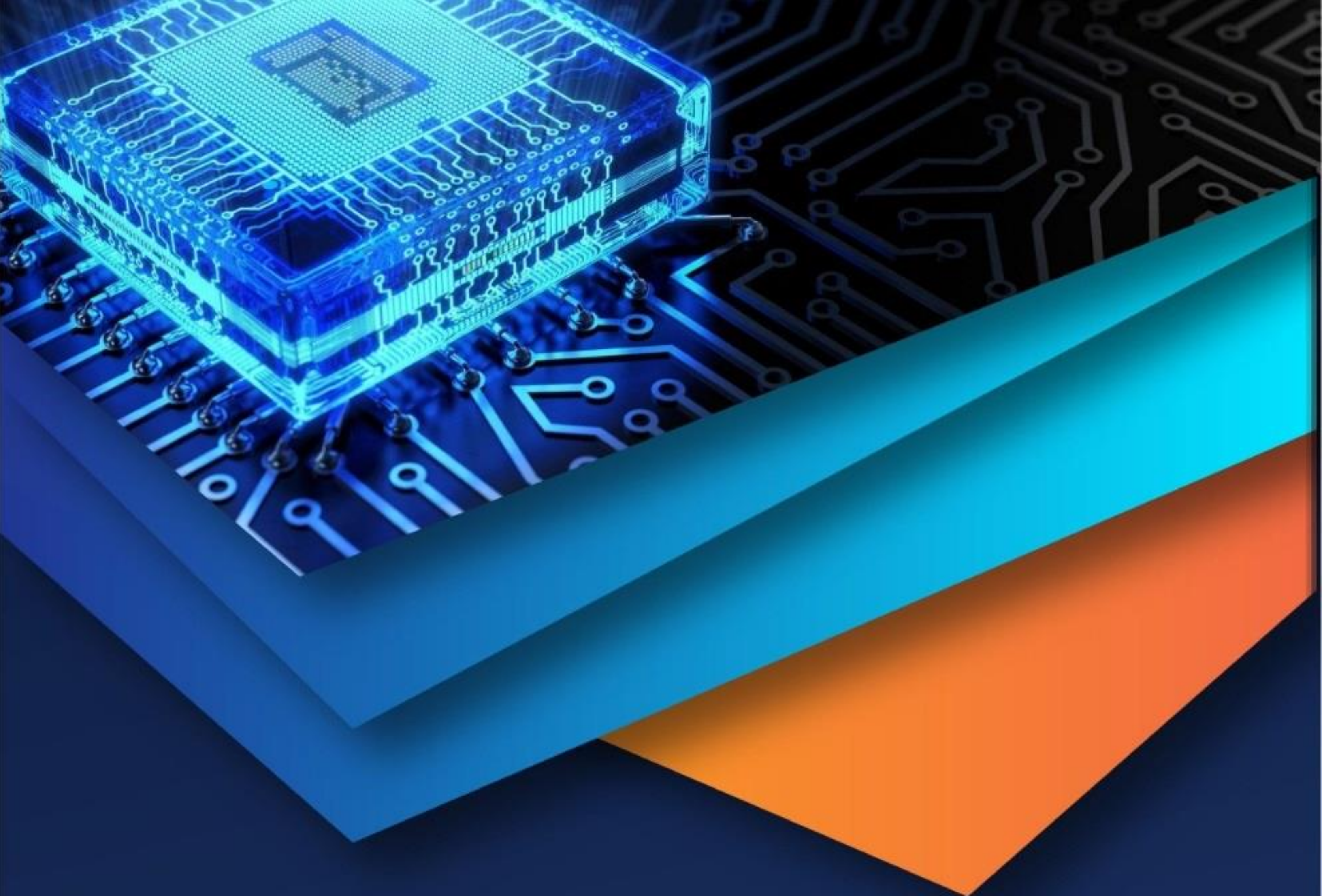

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