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Vehicle-Focused Traffic Mapping for Forecasting Urban Movement and Detecting Peak Congestion Periods

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Abstract- Effectively managing urban traffic dynamics is essential for optimized city planning and administration. This research focuses on a vehicle-centric approach to traffic mapping, aiming to predict congestion levels and identify peak traffic times within urban areas. The main objective is to forecast daily traffic density and detect periods of high congestion to support improved traffic management. To achieve this, we analysed real-time CCTV footage from Nasik Smart City Office, collected from key routes—Pathardi Gaon Circle and Golf Club Ground Circle — over a continuous five-day span. The findings confirm that real-time CCTV data delivers accurate congestion predictions and enhances traffic control strategies. By applying this methodology, we provide a reliable solution for traffic authorities, enabling them to take proactive measures to mitigate traffic congestion and improve overall traffic flow. This research contributes to the advancement of intelligent transportation systems, highlighting the value of incorporating real-time data into urban traffic management solutions.

Index Terms- Live Data Monitoring, Traffic Flow Prediction, Peak Identification

I. INTRODUCTION

In metropolitan settings, effective traffic management is essential for maintaining smooth mobility, ensuring public safety, and promoting environmental sustainability. Efficient traffic control is crucial for reducing congestion, enhancing travel efficiency, and minimizing emissions. However, predicting traffic density remains challenging due to the variability in traffic patterns influenced by factors such as the time of day, the day of the week, and external conditions like weather or local events. This study aims to address these challenges by analyzing video data from two locations in an urban city, connecting significant regions, over a five-day period. The objective is to estimate traffic density and identify peak congestion times. To achieve this, we collected one hour of continuous video footage each day from both locations, capturing data consistently at the same time each day. This approach allows for detailed observation of traffic behaviour and helps pinpoint specific 10-minute intervals within each hour that experience the highest congestion. The focus of the study is on temporal analysis, which enhances the understanding of traffic patterns over various days and times and identifies periods of peak congestion. Additionally, the research explores the use of machine learning techniques to improve the accuracy of traffic density predictions and forecasting models by analyzing complex data patterns. By introducing new methodologies for traffic prediction and congestion management, this study contributes to the development of intelligent transportation systems. The findings offer valuable insights that can inform future traffic management strategies and urban planning efforts.

II. LITERATURE REVIEW

Effective traffic management is vital for contemporary urban infrastructure, targeting reductions in congestion, improvements in safety, and enhancements in overall transportation efficiency. Recent developments in this area have been driven by the adoption of cutting-edge technologies, including real-time monitoring systems, Big Data analytics, and advanced machine learning algorithms, offering novel solutions to the complexities associated with urban traffic control.

The study authored by Mukund Vaidya et al., presents a Raspberry Pi-based solution for real-time monitoring of traffic flow, environmental pollution, and precipitation levels. This system leverages state-of-the-art image processing methods to improve forecasting accuracy. Experimental results demonstrated high precision, underscoring the system's effectiveness in traffic management and environmental monitoring. Proposed future upgrades include the integration of night vision and fog removal technologies to further enhance performance [8].

Dalyapraz Dauletbak and Jongwook Woo examine traffic patterns in Los Angeles County, utilizing a dataset from a navigation platform and processing it with Big Data tools such as Hadoop and Hive. The focus is on congestion prediction through machine learning techniques, with an optimized ARIMA model achieving a micro-average recall of 0.608515 and an overall accuracy of 73.90%. This model proved

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particularly adept at forecasting severe congestion on major highways during peak periods [14].

Alexandra Koutsia et al., describes a real-time vision system incorporating autonomous tracking units and pre- calibrated cameras. Developed under the TRAVIS project, this scalable system employs advanced image processing and data fusion techniques for efficient traffic monitoring and control. Initial evaluations showcased accurate background extraction and real-time traffic management, including speed limit enforcement. Recommendations for future enhancements were provided to further improve system capabilities [13].

Yuanfang Chen et al., investigates traffic flow forecasting using Big Data and machine learning techniques. The review of various predictive models, such as Bayesian Networks, Neural Networks, and ARIMA, highlighted that optimized ARIMA models substantially improve prediction accuracy and decrease RMSE. Utilizing trajectory data from over 2,500 traffic roads, the research demonstrated enhanced traffic flow predictions, contributing to more effective traffic management and congestion mitigation [10].

Yuyan Annie Pan et al., introduces the FD-Markov-LSTM model, combining the fundamental diagram, Markov chain, and LSTM techniques. Evaluated with data from major cities, this hybrid model significantly reduced prediction errors compared to traditional methods like ARIMA, Random Forest, and LSTM, offering superior accuracy in congested traffic scenarios [1].

Soorya V. B. et al., explores the optimization of toll-plaza operations through traffic volume prediction using various models, including SARIMA, Monte Carlo Simulation, Random Forest, and K-Nearest Neighbors. The KNN model demonstrated outstanding performance, highlighting its potential for real-time traffic forecasting within advanced traffic management systems [5].

Parinith R Iyer et al., presents a dynamic traffic signal control system utilizing a camera and Single Shot MultiBox Detector (SSD) for real-time vehicle detection and classification. The system adjusts traffic signal timings based on vehicle counts and classifications, employing a self-correcting algorithm to improve accuracy over time. The study identifies areas for future enhancements, such as improved camera placement and data precision [6].

Vedant Singh et al., addresses urban traffic congestion through an automated system using YOLOv3 for vehicle detection and tracking. This system enhances real-time traffic management and identifies traffic violations by analyzing live CCTV video streams. With a low training loss and effective violation detection, the model has proven beneficial for traffic management, with recommendations for further development, including detecting speeding and helmet use [9].

The reviewed literature highlights significant progress in traffic management through various methodologies, including real-time monitoring, Big Data analytics, and deep learning techniques.

By incorporating advanced technologies such as image processing, machine learning, and predictive modeling, these research contributions provide innovative and adaptable solutions for urban traffic control. Future research is anticipated to address existing gaps and further enhance the effectiveness of these methods across different traffic scenarios.

III. DATA COLLECTION

This research employed primary data sourced from the Nasik Smart City Office using CCTV recordings from two urban locations: Pathardi Gaon Circle and Golf Club Circle, both of which link important sections of the city. Data collection was conducted over five consecutive days, from July 22 to July 26, 2024, with footage captured daily between 11:00 AM and 12:00 noon. Each site was monitored concurrently for one hour per day, ensuring a thorough temporal analysis of traffic trends during the observation period.

The recordings were made in high-definition at a resolution of 1920x1080 pixels and a frame rate of 100 frames per second, allowing for clear and detailed visualization of traffic flow and congestion levels. These technical specifications facilitated precise analysis of vehicle movements, peak traffic periods, and overall traffic density at both sites.

Recognizing the vital role of traffic management, the selected locations and collected data provide critical insights into traffic patterns on key urban routes, supporting an evidence-based approach to improving traffic control measures.

Fig.1. Golf Club Circle

Fig.2. Pathardi Gaon Circle

IV. METHODOLOGY

Our research utilized live CCTV footage from two urban sites: Pathardi Gaon Circle and Golf Club Circle. Data collection was conducted from July 22 to July 26, 2024, with recordings made daily between 11:00 AM and 12:00 noon. These locations were selected due to their notable traffic volume and their role in connecting critical areas of the city. The high-definition footage provided an extensive dataset for our analysis of traffic patterns. The raw footage underwent several preprocessing stages to enhance its clarity and suitability for analysis. Initially, the footage was converted to grayscale to reduce computational complexity. Gaussian blur was then applied to the grayscale images to diminish noise and sharpenobject boundaries.

To isolate moving vehicles from the static background, we applied background subtraction using the Mixture of Gaussians (MOG2) algorithm. The foreground image $I_{\text{fg}}(x, y)$ at pixel (x, y) is computed as follows:

$$I_{\text{fg}}(x, y) = \sum_{i=1}^{N} w_i \cdot \phi_i(x, y)$$

where w_i represents the weight of the i-th Gaussian component, and $\phi_i(x, y)$ is the Gaussian function at pixel (x, y). The background model is updated over time using the formula:

$$F(t) = a \cdot F(t-1) + (1-a) \cdot I(t)$$

where $F(t)$ denotes the updated background model at time t, $F(t-1)$ is the model from the previous time step, $I(t)$ is the current image, and a is the background update rate. Morphological operations, such as dilation and closing, were employed to enhance vehicle detection and eliminate minor noise elements. Dilation is described by:

$$A \quad B = *z \mid (B)_Z \cap A \; G \; \emptyset +$$

where A is the input image and B is the structuring element. Closing, which involves applying dilation followed by erosion, is expressed as:

$$(A \quad B) \quad B$$

These operations facilitated a clearer separation between vehicles and the background. Vehicle detection on the preprocessed footage was achieved using object detection algorithms. Bounding boxes were utilized to outline detected vehicles, with the bounding box BoundingBox(C) for a contour C defined as:

$$\text{BoundingBox}(C) = (x, y, w, h)$$

where (x, y) indicates the top-left corner and (w, h) specifies the dimensions of the bounding box.

The number of vehicles N was calculated for each frame, and traffic density D was determined by:

$$D = \frac{N}{A}$$

where A denotes the monitored area.
Traffic congestion forecasting was based on vehicle counts and traffic density data. By analyzing vehicle movement patterns and density, we identified congestion trends and predicted periods of elevated congestion. Periods of high congestion were identified through a temporal analysis of traffic density data. Specific thresholds for vehicle counts and flow rates were set to pinpoint the 10-minute intervals within each hour with the highest congestion. This analysis provided insights into peak traffic times and patterns observed during the study.

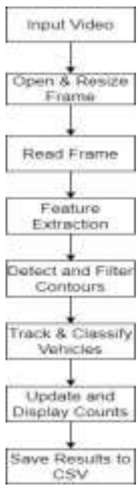

Fig.3. System Architecture

The effectiveness of the vehicle detection and traffic analysis methods was evaluated by comparing predicted traffic patterns to the actual observed data. Standard evaluation metrics, such as accuracy, precision, and recall, were used to gauge the performance of the detection algorithms and traffic prediction methods.

Our study employed advanced computer vision frameworks and statistical analysis tools to enhance data processing, vehicle detection, and traffic density assessment. Specifically, we used OpenCV, a comprehensive computer vision library, for tasks such as background subtraction, contour detection, and object tracking. OpenCV's cv2.VideoCapture and background subtractor algorithms

(cv2.bgsegm.createBackgroundSubtractorMOG) were crucial for processing video frames and detecting vehicles. Additionally, NumPy was utilized for numerical computations and array manipulations, facilitating image transformations and matrix operations essential for dilation and morphological processing. These tools collectively ensured that our methodologies were rigorous and precise, enabling accurate predictions of traffic congestion and identification of peak congestion periods.

V. EXPERIMENTAL DESIGN

Our research employed video footage captured from a stationary roadside camera to monitor real-time traffic conditions. This video data served as the primary resource, facilitating the evaluation of vehicle detection algorithms and traffic density assessments. To enhance processing efficiency, all videos were resized to 1200x720 pixels. The video frames underwent a series of preprocessing techniques to improve the accuracy of vehicle detection. Initially, frames were converted to grayscale to reduce computational complexity while preserving critical features. Gaussian blurring was applied to mitigate noise, thereby allowing for clearer identification of moving vehicles. The MOG2 background subtraction method was utilized to differentiate vehicles from the static background. Additionally, morphological operations, including dilation and closing, were conducted to merge fragmented vehicle contours, enhancing overall object detection.

Contours were extracted from the processed frames, and bounding boxes were utilized to identify potential vehicles. The central coordinates of each vehicle were computed for tracking purposes, with a visual representation provided using circles for better clarity. Traffic density was evaluated by drawing a line across each frame, and vehicles crossing this line were counted. Based on established thresholds, traffic density was categorized as low (≤15 vehicles), moderate (16-30 vehicles), or high (>30 vehicles). Real-time vehicle counts and traffic density classifications were displayed directly on the video feed, offering immediate insights into traffic conditions.

A congestion prediction model was created based on vehicle counts and density classifications. This model monitored real-time traffic conditions and indicated congestion levels by analyzing vehicle frequency and density. Periodic data collection enabled further analysis and validation of traffic patterns. Data was recorded in Excel every 30 seconds to ensure precision in results. Subsequently, all 20 values collected at 30-second intervals were aggregated into 10-minute segments, yielding six values for each 10-minute period. The effectiveness of the vehicle detection and traffic density assessment system was assessed by comparing automated vehicle counts with manually verified counts from the video footage. The reliability of the traffic density classification was tested under various traffic conditions to ensure consistency. The system's frame processing times were also monitored to confirm its capability to operate in real-time.

Several tools and technologies were employed to implement the system. Python was utilized as the primary programming language for algorithm development, while NumPy facilitated the numerical operations essential for image processing. Pandas played a pivotal role in data management, enabling efficient storage and analysis of vehicle counts and traffic density information. The system was deployed on a machine equipped with an NVIDIA GeForce GTX 1650 Ti GPU to enhance processing speed and efficiency.

VI. RESULTS

The traffic patterns observed at both Golf Club Circle and Pathardi Gaon Circle, as presented in Table I and Table II, respectively, over the five-day period, provide key insights into vehicle flow and density fluctuations during the one-hour timeframe.

Golf Club Circle Analysis: In Fig.4., the bar plot reveals that the highest vehicle count occurs during the initial 10- minute interval from 11:00 AM to 11:10 AM, reaching approximately 1,000 vehicles, followed by a gradual decline. The accompanying line plot indicates frequent fluctuations in traffic density, oscillating between high and moderate levels throughout the observed timeframe. On Tuesday, represented in Fig. 5., a similar trend is noted, with the bar plot showing a peak in the first 10-minute interval, followed by a steady decline. The line plot further illustrates significant fluctuations in traffic density, reflecting a dynamic and inconsistent flow. Wednesday's data in Fig.6. again demonstrates the highest vehicle count during the initial interval, with a consistent decline thereafter. The line plot shows frequent changes between high and moderate traffic density, underscoring the erratic nature of the traffic pattern.

In Fig.7. for Thursday, the bar plot indicates a prominent initial peak, which is followed by a steady decrease. The line plot continues to display notable fluctuations, suggesting variable traffic flow throughout the period. Finally, in Fig.8. for Friday, the bar plot indicates the highest vehicle count during the last 10- minute interval, from 11:50 AM to 12:00 noon. The line plot for Friday reveals frequent fluctuations in traffic density, with peak values occurring later in the observed period compared to the other days.

Table 1: Golf Club Circle Vehicles Count

Date	11:10	11:20	11:30	11:40	11:50	12:00
22/07/24	531	310	228	203	158	513
23/07/24	1044	523	658	485	338	371
24/07/24	1257	560	290	483	324	305
25/07/24	1167	762	450	410	394	352
26/07/24	1073	619	486	347	372	291

Table 2: Pathardi Gaon Circle Vehicles Count

Date	11:10	11:20	11:30	11:40	11:50	12:00
22/07/24	787	378	418	602	547	654
23/07/24	853	693	505	422	609	757
24/07/24	961	484	668	368	643	384
25/07/24	1019	757	481	552	553	559
26/07/24	680	461	259	203	429	237

Pathardi Gaon Circle Analysis: On Monday, as shown in Fig.9., the highest vehicle count is recorded during the initial 10-minute interval from 11:00 AM to 11:10 AM, followed by a gradual decline. The line plot reflects frequent fluctuations in traffic density between high and moderate levels, highlighting an inconsistent flow. Fig.10. for Tuesday illustrates a peak in the initial interval, with a gradual decrease thereafter.

The line plot demonstrates substantial fluctuations in traffic density, indicating a dynamic traffic situation. On Wednesday, represented in Fig.11., the bar plot shows the highest vehicle count during the first 10-minute interval, again followed by a steady decline. The line plot reveals frequent changes between high and moderate traffic density, emphasizing the inconsistent traffic pattern. In Fig.12. for Thursday, the bar plot indicates a significant initial peak, followed by a decline.

The line plot continues to exhibit notable fluctuations, suggesting varying traffic flow. Finally, in Fig.13. for Friday, a distinct pattern emerges, with the bar plot revealing the highest vehicle count in the final interval from 11:50 AM to 12:00 noon. The line plot shows frequent fluctuations in traffic density, indicating a dynamic and inconsistent traffic flow.

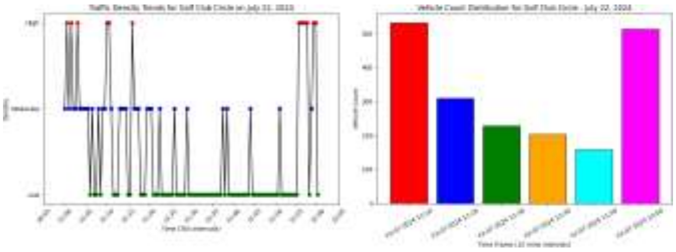

Fig.4. Traffic Analysis for Golf Club Circle on July 22,2024

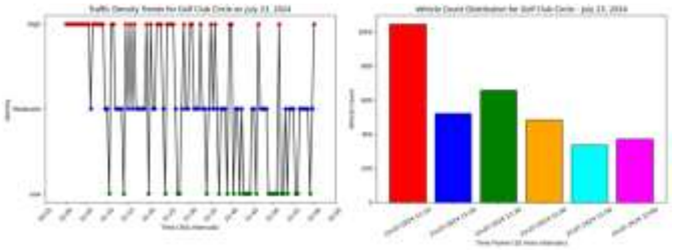

Fig.5. Traffic Analysis for Golf Club Circle on July 23, 2024

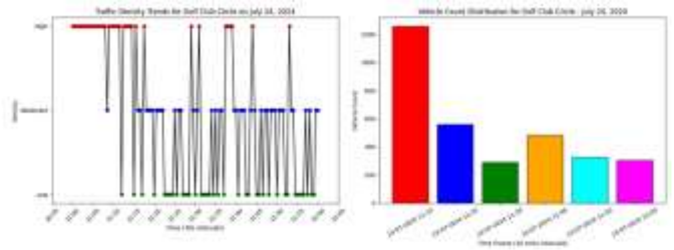

Fig.6. Traffic Analysis for Golf Club Circle on July 24, 2024

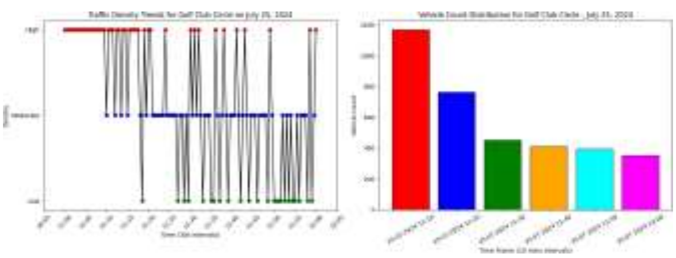

Fig.7. Traffic Analysis for Golf Club Circle on July 25, 2024

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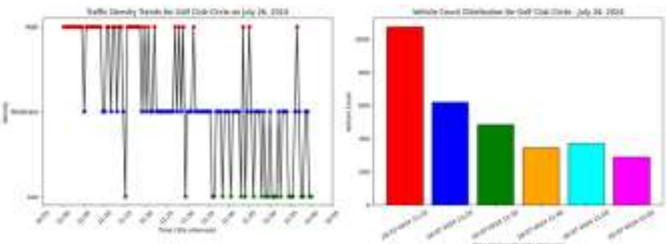
Fig.8. Traffic Analysis for Golf Club Circle on July 26, 2024

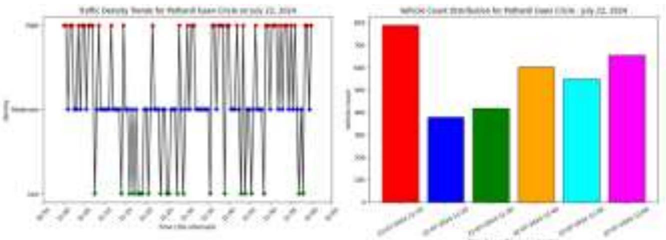
Fig.9. Traffic Analysis for Pathardi Gaon Circle on July 22, 2024

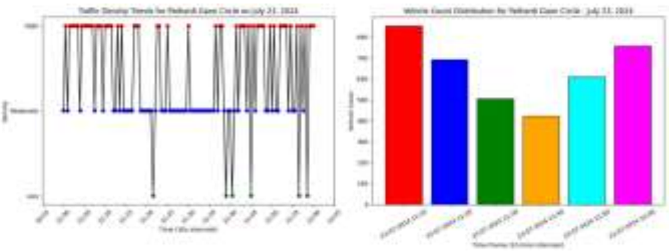
Fig.10. Traffic Analysis for Pathardi Gaon Circle on July 23, 2024

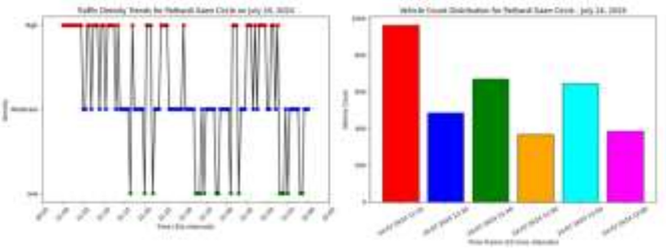
Fig.11. Traffic Analysis for Pathardi Gaon Circle on July 24, 2024

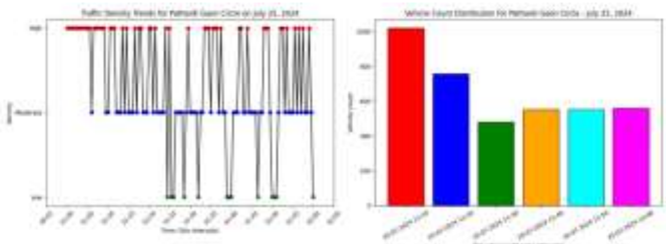
Fig.12. Traffic Analysis for Pathardi Gaon Circle on July 25, 2024

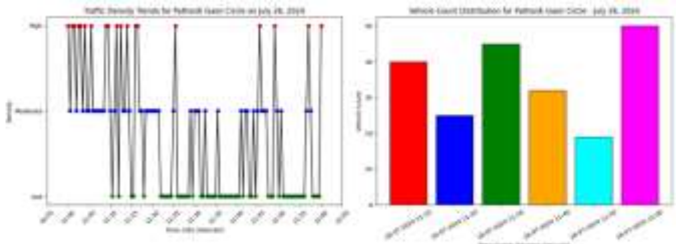
Fig.13. Traffic Analysis for Pathardi Gaon Circle on July 26, 2024

Fig.14. Output for Golf Club Circle

Fig.15. Output for Pathardi Gaon Circle

VII. CONCLUSION

In summary, the examination of traffic patterns at Golf Club Circle and Pathardi Gaon Circle as shown in Fig.14. & Fig,15., repectively, revealed clear peak traffic periods and significant variations in vehicle density. These findings indicate that traffic management can optimize signal timings according to vehicle counts to effectively reduce congestion. Furthermore, this research highlights the capacity to anticipate traffic conditions, facilitating more proactive management approaches. By employing real-time video analytics, urban planners and traffic authorities can make well-informed, data-driven decisions, ultimately enhancing traffic flow and promoting more efficient urban planning. This study illustrates the importance of utilizing analytics in tackling urban traffic issues.

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