DYNAMIC TRAFFIC TOLLING PREDICTION USING SOFT COMPUTING AND OPEN CV

Lolakshi P K[1], chnadana A S[2], Madhu M[3], Meghana K[4], Varsha A M[5]

[1,2,3,4,5] Department of Information Science and Engineering, AIET, Mijar, Dakshina Kannada, India

lolakshi@aiet.org.in[1], chandanaas89@gmail.com[2], madhumadhu27836@gmail.com[3], meghanakodappa@gmail.com[4], varsh3569@gmail.com[5]

ABSTRACT

In response to the rapid urbanization and escalating vehicular traffic, smart city initiatives have become imperative for fostering sustainable urban development. Urban planners grapple with myriad challenges, chief among them being the effective management of traffic congestion. This congestion not only undermines transportation system efficiency but also precipitates environmental degradation and economic losses.

Dynamic traffic tolling emerges as a promising solution to alleviate congestion by dynamically adjusting toll prices based on real-time traffic conditions. However, the effective implementation of dynamic tolling hinges on accurate prediction models to anticipate traffic patterns and optimize tolling strategies.

This research project proposes a novel method to predict traffic flow in smart cities using computational software. Leveraging computational software techniques such as neural networks, fuzzy logic, and genetic algorithms offers the flexibility needed to model nonlinear relationships in traffic dynamics. The project aims to develop powerful predictive models capable of accurately and efficiently forecasting traffic and congestion levels. By leveraging the power of software calculations, this endeavor seeks to provide urban planners with indispensable tools to enhance traffic management strategies and promote more sustainable urban environments.

Keywords—Deepsort, Pychart, numpy

I INTRODUCTION

This research initiative involves the acquisition of real-time traffic data from diverse sources such as sensors, GPS devices, and traffic cameras to construct a comprehensive dataset for model development, training, and practical application. Leveraging this data, fuzzy electronics will be employed to capture temporal and spatial traffic patterns, while fuzzy logic will facilitate the integration of imprecise and uncertain information into forecasting methodologies. Additionally, genetic algorithms will be utilized to optimize models and enhance prediction accuracy.

The proposed methodology for assessing traffic congestion will undergo rigorous evaluation via simulations and case studies within an urban setting. Key performance metrics including prediction accuracy, computational efficiency, and scalability will be meticulously analyzed to ascertain the efficacy of the proposed approach. Furthermore, potential economic ramifications stemming from transportation electrification strategies, travel behavior dynamics, and environmental sustainability considerations will be systematically examined to offer actionable insights to policymakers and urban planners.

Ultimately, this research endeavor is dedicated to advancing transportation systems within smart cities, thereby fostering the implementation of more efficient and effective solutions. By seamlessly integrating software technology into traffic forecasting methodologies, this project presents a valuable tool to optimize urban traffic management and engender improved urban environments.

Furthermore, the adoption of fast traffic cost estimation utilizing OpenCV presents a promising avenue for smart city traffic management. By integrating OpenCV computer vision technology, this innovative solution enables real-time analysis of traffic incidents captured by citywide camera networks. Continuously streaming data from these cameras undergoes image processing techniques to identify vehicles, track their movements, and ascertain vehicle speeds. Leveraging machine

learning algorithms trained on historical traffic data, the system can anticipate future traffic levels and dynamically adjust tolls accordingly.

This approach not only enhances traffic flow by incentivizing drivers to alter routes or travel times but also optimizes toll fares to bolster revenue for transportation authorities. Moreover, dynamic fare forecasting contributes to the long-term resilience of urban transportation systems by promoting sustainable transport practices and curbing carbon emissions.

As cities grapple with the multifaceted challenges of urbanization and transportation, the adoption of traffic cost estimation methodologies emerges as a pivotal tool to enhance efficiency, sustainability, and overall quality of life for urban residents.

II MODELS AND LIBRARIES USED

A YOLOV8

In the realm of computer vision, the advent of YOLOv8, a state-of-the-art deep learning model, has heralded a transformative era in real-time object recognition. With its pioneering design and cutting-edge technology, YOLOv8 has redefined the landscape of product search, delivering unparalleled accuracy and efficiency in dynamic scenarios. Its impact transcends industries, finding applications in robotics, autonomous driving, and video surveillance, where the ability to swiftly identify objects bears profound implications for safety and decision-making processes.

The architecture of YOLOv8 harnesses the synergy of computer vision technology and machine learning algorithms to swiftly and precisely detect and localize objects within images and videos. Originating from the seminal research paper "You Only Look Once: Exploring the Realm of Time" authored by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi in 2015, YOLO (an acronym for "You Only Look Once") has emerged as a pivotal milestone in real-time object detection.

Since its inception, YOLO has undergone significant evolution, each iteration building upon its predecessors' advancements. The inaugural version, YOLOv1, introduced the ground breaking concept of true object detection by partitioning the input image into a grid and predicting bounding boxes along with class values, enabling simultaneous detection of multiple objects. Subsequent iterations, including YOLOv2 and YOLOv3, further enhanced the model's functionality by integrating techniques such as anchor boxes, feature pyramid networks, and

increased prediction capabilities, resulting in notable improvements in both accuracy and speed.

Today, the pinnacle of the YOLO series is embodied in YOLOv8, marking a watershed moment in real-time asset discovery. YOLOv8 empowers researchers and developers alike to achieve unparalleled levels of accuracy and speed in object detection tasks, positioning it as the premier choice for applications in robotics, autonomous driving, and video surveillance.

Version	Year	Advancement
YOLOV1	2015	Introduction to grid-based discovery method
YOLOV2	2016	Multi-scale prediction, feature pyramid networks, and anchor boxes are included.
YOLOV3	2018	Increased speed and accuracy following the deployment of Darknet-53 and Numerous detection scales
YOLOV3	2021	A cutting- edge deep learning model called YOLOv8 was created for computer vision applications requiring real-time object recognition

B DEEP SORT

DeepSORT, an acronym for Deep Simple Online Realtime Tracking with a Deep Association Metric, represents a revolutionary tracking algorithm predominantly employed within computer vision and object detection domains, notably in the sphere of multi-object tracking (MOT). Although not inherently geared towards traffic prediction, the seamless integration of DeepSORT into expansive traffic prediction and management frameworks heralds a new era of predictive analytics in urban mobility.

Object Detection and Tracking:
DeepSORT distinguishes itself by its unparalleled proficiency in real-time tracking of multiple objects, seamlessly adapting to the dynamic nature of live traffic environments. Leveraging its capabilities, DeepSORT can meticulously monitor vehicle movements in live traffic camera feeds or recorded videos, furnishing indispensable data on vehicle trajectories, speeds, and interactions. Such granular insights are instrumental in dissecting intricate traffic patterns and formulating predictive models.

Data Collection and Analysis:
A continuous deluge of data streams emanates from DeepSORT, encapsulating the minutiae of vehicle movement and behavior. This wealth of information serves as the cornerstone for identifying trends, congestion hotspots, and traffic flow dynamics. Through rigorous analysis, traffic engineers and planners glean invaluable insights into peak hours, recurring congestion, and other pertinent factors shaping traffic behavior, thereby refining predictive models for enhanced accuracy.

Integration with Prediction Models:

While DeepSORT refrains from direct predictive functions, its output—comprising meticulously tracked vehicle data—serves as a veritable goldmine for predictive modeling endeavors. By harnessing diverse techniques such as machine learning, statistical analysis, or mathematical modeling, prediction models leverage DeepSORT-derived vehicle trajectories to prognosticate future traffic conditions. Empowered with such insights, these models furnish informed forecasts on traffic volume, congestion levels, travel times, and other salient parameters.

Real-time Traffic Management:
Operating seamlessly in real-time, DeepSORT furnishes instantaneous feedback on prevailing traffic conditions, offering a vital component for real-time traffic management frameworks. When amalgamated with prediction models, DeepSORT affords traffic authorities the agility to dynamically adjust traffic signals, reroute traffic, or implement other interventions to mitigate congestion and optimize traffic flow—a paradigm shift in urban mobility management.

In essence, while DeepSORT may not inherently embody a traffic prediction algorithm, its pivotal role in providing precise and reliable tracking data resonates profoundly within traffic prediction ecosystems. By seamlessly integrating DeepSORT into traffic prediction frameworks, cities and transportation authorities stand poised to elevate their predictive capabilities, thus fostering improved urban mobility and congestion mitigation—a testament to the transformative potential of cutting-edge technology in urban planning and management.

C OPEN CV

OpenCV, an abbreviation for Open Source Computer Vision Library, stands as a formidable ally in the realm of computer vision, wielding vast capabilities for a myriad of applications, including the intricate domain of traffic prediction within smart cities. Herein lies a glimpse into the multifaceted role of OpenCV in the art of traffic forecasting:

Vehicle Detection and Tracking:
OpenCV's arsenal of functions and algorithms burgeons with prowess in vehicle detection and tracking, pivotal for ensuring vehicular maintenance in critical junctures. Leveraging techniques such as Haar steps, Histogram of Oriented Gradients (HOG), or the formidable convolutional neural networks (CNN), OpenCV adeptly identifies vehicles within images or video streams. Once identified, OpenCV embarks on a journey of tracking the vehicles' trajectories over time, endowing traffic prediction with invaluable insights.

Traffic Analysis:
Delving into the intricate labyrinth of traffic patterns, OpenCV dissects the movement and conduct of detected and tracked vehicles. With precision akin to that of a seasoned conductor, OpenCV discerns parameters such as vehicle speed, acceleration, lane availability, and traffic intensity. These insights serve as the bedrock for comprehending prevailing traffic dynamics and prophesying future traffic scenarios.

Anomaly Detection:
OpenCV's vigilant gaze extends to the detection of anomalies or aberrant occurrences within traffic landscapes, be it collisions, road impediments, or abrupt traffic fluctuations. Swift detection via OpenCV triggers alerts or notifications to traffic control authorities, paving the way for expeditious responses aimed at curbing disruptions and enhancing traffic flow.

Data Collection and Preprocessing:
In the pursuit of honing predictive prowess, OpenCV aids in the collection, preprocessing, and optimization of requisite traffic data. Armed with functionalities for image and video processing, OpenCV seamlessly assimilates real-time data from vehicle monitoring systems. Furthermore, OpenCV lends its hand to data augmentation techniques, fostering diversity and robustness within training

datasets, thus bolstering the predictive capabilities of traffic models.

Integration with Machine Learning Models:
The symbiotic relationship between OpenCV and machine learning frameworks—be it TensorFlow, PyTorch, or its kindred spirits—ushers forth a new era of predictive prowess. Through amalgamation with machine learning algorithms, OpenCV's detection and tracking capabilities converge with predictive models, enabling the forecasting of future traffic scenarios based on historical data and real-time analysis.

Visualization and User Interface:
OpenCV's visualization prowess unfurls a tapestry of traffic data and forecasts, fostering a deeper understanding among users. Real-time traffic metrics, ranging from traffic volumes to predictive analytics, find expression through OpenCV's programming capabilities, empowering drivers and decision-makers with the tools to monitor and manage traffic with finesse.

D PYTROCH

PyTorch, an illustrious deep learning framework, emerges as a beacon of promise in the realm of traffic congestion prediction within smart cities, harnessing the formidable prowess of neural networks to wield accuracy and efficiency with unparalleled finesse. Behold, the myriad ways in which PyTorch is harnessed:

Diverse Deep Learning Models:
PyTorch unfurls a tapestry of deep learning architectures, including the stalwarts of convolutional neural networks (CNN), recurrent neural networks (RNN), Long Short Term Memory Network (LSTM), and the transformative Transformer. These formidable models undergo rigorous training on historical traffic data, unraveling the intricate tapestry of interdependencies that govern traffic dynamics.

Temporal Data Processing:
The heartbeat of traffic forecasting pulsates with the rhythm of real-time data, encompassing a symphony of traffic flow, congestion levels, and temporal travel patterns. PyTorch's innate prowess in integrated modeling heralds an era of efficient processing, with RNNs and LSTMs orchestrating a ballet of sequential data processing, capturing the ephemeral nuances inherent in traffic patterns.

Feature Representation Learning:
PyTorch unlocks the latent potential of deep learning models to distill salient features from raw inputs, a veritable boon in the tumultuous realm of traffic forecasting. Amidst the capricious interplay

between inputs—ranging from traffic volume to weather conditions—PyTorch empowers models to glean insights, transcending the realm of predictability and embracing the ineffable complexities of traffic prediction.

Customization and Experimentation:
A crucible of innovation unfurls within PyTorch's dynamic computational graph and pliable architecture, affording researchers and practitioners the canvas to sculpt bespoke models tailored to the idiosyncrasies of dynamic traffic prediction. Here, experimentation knows no bounds, as diverse network architectures, loss functions, and optimization algorithms converge in a symphony of innovation.

Parallel and Distributed Computing:
PyTorch unfurls its wings in the realm of parallel and distributed computing, scaling the lofty peaks of big data to tackle the Herculean challenge of training complex neural networks on gargantuan traffic datasets. This capability serves as a linchpin in the quest to surmount the obstacles that bedevil traffic prediction in smart cities.

Integration with Python Libraries:
PyTorch stands as a harmonious ensemble player in the orchestra of Python libraries, seamlessly integrating with NumPy, pandas, scikit-learn, and Matplotlib. This symbiotic relationship fosters a holistic ecosystem, nurturing the seeds of data preprocessing, infrastructure development, evaluation, and visualization, pivotal components within the predictive pipeline.

E NUMPY

NumPy, a venerable stalwart in the realm of Pythonic computations, emerges as a quintessential tool in the pursuit of unraveling the enigmatic tapestry of traffic prediction within smart cities. Behold, the manifold facets of NumPy's utility in this noble endeavor:

Data Representation and Management:
NumPy unfurls a rich tapestry of data structures, including arrays and matrices, providing an idyllic canvas for encapsulating the myriad nuances of traffic dynamics—from flow rates to vehicular speeds. This robust data structure facilitates seamless storage and manipulation of copious volumes of data, streamlining operations such as preprocessing, extraction, and model formulation.

Mathematical Wizardry:
Within NumPy's hallowed halls lie an array of mathematical functions, poised to decipher the intricate rhythms of traffic data. Functions such as mean, median, and standard deviation, serve as the

harbingers of insight, unveiling hidden patterns lurking within the labyrinthine corridors of traffic datasets. Furthermore, NumPy's pantheon of linear algebra functions lends credence to estimations algorithms, enabling the orchestration of matrix operations and eigenvalue decompositions with consummate ease.

Statistical Sagacity:
NumPy's arsenal is replete with statistical functions, serving as the compass in the vast expanse of traffic data. Histogram calculations, probability density estimations, and regression analyses serve as the lodestars, illuminating the path towards understanding the intricate interplay between traffic variables and predictive features. Through the lens of statistical analysis, NumPy unveils the latent patterns embedded within traffic data, paving the way for the development of robust predictive models.

Time Series Mastery:
Traffic data, akin to a symphony, unfolds as a temporal saga, beckoning the need for time series analysis. NumPy's arsenal boasts tools tailored for this very purpose—sliding window functions, delayed feature renderings, and automatic correlation analyses stand as sentinels, safeguarding against the tempestuous tides of temporal data. Through these tools, NumPy unveils the rhythmic cadence of historical traffic data, offering insights crucial for training predictive models.

Standardization and Validation:
NumPy assumes the mantle of arbiter in the realm of standardization and validation, furnishing functions for calculating performance metrics—squared errors, mean absolute errors, and R-squared scores stand as the barometers of predictive efficacy. Armed with these metrics, traffic engineers and data scientists navigate the labyrinth of prediction models, discerning the most efficacious algorithms for smart city traffic management.

Integration with Machine Learning Libraries:
NumPy seamlessly integrates with a pantheon of machine learning libraries, including scikit-learn and TensorFlow, heralding a harmonious symphony of predictive prowess. NumPy arrays serve as the bedrock for machine learning models, facilitating the development of predictive models ranging from regression to classification, culminating in a crescendo of urban mobility optimization.

III DATASETS AND RESULT

Utilizing OpenCV's computer vision capabilities, our dynamic traffic tolling prediction system effectively analyses real- time traffic patterns. Through continuous monitoring of traffic cameras, the system processes live video feeds to extract relevant data for predicting congestion levels. For predicting the traffic, we use videos figure 3.1 shows one of the frame from dataset video.

Figure 3.1 image taken from input video

The yolo algorithm is used to recognising the objects in the video. First the video is converted into number of frames. There are totally 5396 frames are generated from the video. Figure 3.2 will shows the one of the frame from the video.
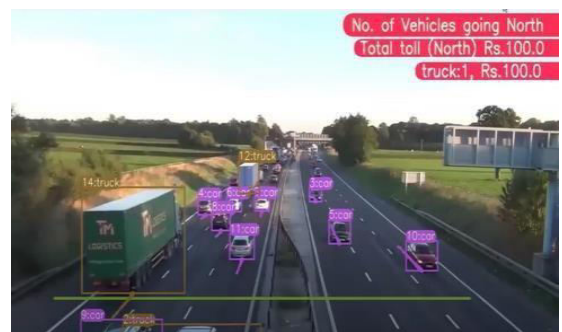

Figure 3.2 frame generated from the video

We will provide one user interface so that user can get information about the traffic then they will decide in which route they can take. The Figure 4.3 will show that the toll rate for different toll rates for different type of vehicles. Toll rate will vary according to the number of vehicles.

Figure 3.3 user interface image

IV CONCLUSION

In the grand tapestry of urban dynamics, the art of dynamic traffic toll estimation, propelled by the ethereal realms of software calculation methodologies, stands as a beacon of hope in the relentless quest for traffic congestion mitigation and toll strategy optimization. Through a harmonious amalgamation of machine learning, fuzzy logic, neural networks, and sundry software computing marvels, the veritable oracle of accurate traffic pattern prognostication and demand divination is unfurled, empowering authorities to orchestrate toll rate adjustments with surgical precision, thus sculpting the landscape of urban mobility with finesse while concurrently augmenting revenue streams.

At the heart of this transformative paradigm lies the quintessential advantage of software-driven traffic forecasting—the innate capacity to navigate the labyrinthine corridors of traffic systems, bedecked with intricate interrelationships, uncertainties, and non-linearities. By harnessing the wealth of historical traffic data, real-time monitoring insights, and atmospheric vagaries such as weather conditions, the computational model metamorphoses, evolving in tandem with the ebb and flow of change, thereby bequeathing unto humanity a bastion of steadfast and reliable predictions.

Moreover, the advent of electronic tolling systems, in consonance with industry standards, heralds a boon for commuters and transportation entities alike. Passengers revel in the bliss of diminished voyages and heightened temporal efficacy, whilst transportation conglomerates optimize infrastructure utilization, curtail environmental repercussions, and cultivate revenue streams akin to an ever-flowing fountain of prosperity.

Yet, amidst the iridescent tapestry of opportunity, lurk the shadows of challenges and contemplations, demanding prudent consideration in the implementation of dynamic toll prediction. The imperatives of meticulous data collection, refined design standards, equitable pricing paradigms, and seamless integration with existing transportation frameworks loom large, beseeching the collective wisdom of stakeholders to navigate the labyrinth of complexities and chart a course towards urban transportation nirvana.

In summation, the saga of dynamic traffic toll estimation, woven with the threads of software calculation methodologies, beckons urban transportation towards the shores of greater efficiency, sustainability, and resilience. The symphony of progress, underscored by ceaseless research, innovation, and collaboration amongst academic luminaries, corporate titans, and governmental stewards, emerges as the panacea for the multifarious transportation quandaries besieging contemporary cities.

V REFERNCES

[1] V. Kovalev, A. Kalinovsky, and V. Liauchuk, ''Deep learning in big image data: Histology image classification for breast cancer diagnosis,'' in Proc. Int. Conf. BIG DATA Adv. Anal. (BSUIR), Jun. 2016, pp. 44–53.

[2] E. Strubell, A. Ganesh, and A. McCallum, ''Energy and policy consid erations for deep learning in NLP,'' in Proc. 57th Annu. Meeting Assoc. Comput. Linguistics, 2019,pp. 3645–3650.

[3] H. Mao, S. Yao, T. Tang, B. Li, J. Yao, andY. Wang, ''Towards real time object detection on embedded systems,'' IEEE Trans. Emerg. Topics Comput., vol. 6, no.3, pp. 417–431, Jul. 2018, doi:10.1109/TETC. 2016.2593643.

[4] J. A. Carballo, J. Bonilla, M. Berenguel, J. Fernández-Reche, and G. García, ''New approach for solar tracking systems based on computer vision, low cost hardware and deep learning,'' Renew. Energy, vol. 133,pp. 1158–1166, Apr. 2019.

[5] B. Moons, D. Bankman, and M. Verhelst, ''Embedded deep learning,'' in Algorithms, Architectures and Circuits for Always-on Neural Network Processing. Cham, Switzerland: Springer, 2019, doi: 10.1007/978-3-319- 99223-5.

[6] K. Rungsuptaweekoon, V. Visoottiviseth, and R. Takano, ''Evaluating the power efficiency of deep learning inference on embedded GPU systems,'' in Proc. 2nd Int. Conf. Inf. Technol. (INCIT), Nov. 2017,pp.1–5,doi:10.1109/INCIT.2017.8257866.

[7] G. Plastiras, C. Kyrkou, and T. Theocharides, ''Efficient ConvNet-based object detection for unmanned aerial vehicles by selective tile pro cessing,'' in Proc. 12th Int. Conf. Distrib. Smart Cameras, Sep. 2018, pp. 1–6.

[8] O. Rukundo, ''Effects of image size on deep learning,'' 2021, arXiv:2101.11508.