PROJECTREPORT

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1.INTRODUCTION

1.1 ProjectOverview

The Traffic Intelligence project aims to revolutionize traffic management through the implementation of advanced machine learning techniques for accurate and real-time traffic volumeestimation.Withtheever-increasingurbanizationandtheriseinthenumberofvehicles on the road, understanding and managing traffic patterns have become crucial for efficient urban planning and transportation systems.

1. ProjectObjectives:

- Developarobustmachinelearningmodelfortrafficvolumeestimation.
- Implementreal-timedataacquisitionmethodsforcontinuousmodelimprovement.
- Enhanceaccuracyandreliabilitythroughtheintegrationofmultipledatasources.
- Provideauser-friendlyinterfaceforstakeholderstoaccessandinterprettrafficdata.

2. Methodology:

- DataCollection:Gatherreal-timetrafficdatafromvarioussources,includingcameras, sensors, and historical records.
- FeatureEngineering:Identifyrelevantfeaturessuchastimeofday,weatherconditions, and special events that may impact traffic volume.
- Machine Learning Model: Train a machine learning model (e.g., neural network, regressionmodels)usinglabeleddatatopredicttrafficvolumebasedontheselected features.
- Real-TimeIntegration:Implementmechanismsforcontinuousdatafeedtoupdateand refine the model in real-time.

3. ExpectedOutcomes:

- Accurateandtimelytrafficvolumepredictionsforvariouslocations.
- Improvedtrafficmanagementcapabilitiesforurbanplannersandtransportation authorities.
- Enhanceddecision-makingthroughinsightsderivedfromtheanalysisoftrafficpatterns.

4. SignificanceoftheProject:

- ●UrbanPlanning:Assistcityplannersinmakinginformeddecisionsforinfrastructure development and traffic management.
- ●ResourceOptimization:Optimizetheallocationofresourcessuchastrafficsignals,law enforcement, and emergency services.
- ●EnvironmentalImpact:Contributetoreducedfuelconsumptionandemissionsby optimizing traffic flow.

5. Challenges:

- ●DataQualityandIntegration:Ensuringthereliabilityandseamlessintegrationofdiverse data sources.
- ●ModelAdaptability:Developingamodelthatcanadapttodynamicchangesintraffic patterns.
- ●PrivacyConcerns:Addressingprivacyissuesrelatedtothecollectionanduseoftraffic data.

1.2Purpose

The"TrafficIntelligence-AdvancedTrafficVolumeEstimationusingMachineLearning" project serves a crucial purpose in modern urban infrastructure by addressing the challengesinherentintrafficmanagement.Atitscore,theprojectaimstooptimizethe efficiency of traffic control systems through the deployment of advanced machine learningtechniques.Byprovidingaccurateandreal-timetrafficvolumeestimations,the project seeks to empower decision-makers, urban planners, and transportation authorities with invaluable data-driven insights. This, in turn, facilitates informed decision-making for resource allocation and infrastructure development. The project's ultimategoalistoenhancetheoverallefficiencyoftrafficmanagement,contributingto optimized resource allocation, reduced congestion, and improved environmental sustainability.Thedevelopmentofauser-friendlyinterfaceensuresthatstakeholders can easily access and interpret the traffic data, making it a valuable tool for both professionalsandthewidercommunityinvolvedinurbanplanningandtransportation.

2.LITERATURESURVEY

2.1 ExistingProblem

1.InaccurateTrafficPredictions:

○Existingtrafficmanagementsystemsoftenrelyonhistoricaldataandfixed algorithms, resulting in inaccuracies, particularly in rapidly changing urban environments.

2.LimitedReal-TimeAdaptability:

○Currentsystemslacktheabilitytoadaptinreal-timetosuddenchangesintraffic conditions,suchasaccidentsorroadclosures,leadingtosuboptimaltrafficflow.

3.DataFragmentation:

○Trafficdataiscollectedfromvarioussources,creatingfragmentationand difficulties in integrating information, preventing the development of a comprehensive and accurate traffic model.

4.StaticAlgorithms:

○Manysystemsusestaticalgorithmsthatdonotaccountforthedynamicnature of traffic patterns, resulting in less effective traffic management.

5.InsufficientResponsetoEvents:

○Currentsystemsoftenstruggletorespondeffectivelytounexpectedevents,such as special occasions or emergencies, leading to disruptions in traffic flow.

6.InefficientInfrastructurePlanning:

○Limited accuracy in traffic predictions hampers effective urban planning, potentiallyleadingtoinadequateinfrastructuredevelopmenttoaccommodate changing traffic needs.

7.EnvironmentalImpact:

○Ineffectivetrafficmanagementcontributestoincreasedfuelconsumptionand emissions due to congestion, negatively impacting the environment.

8.UserExperienceIssues:

○Commutersoftenexperiencefrustrationanddelaysduetothelimitationsof existingtrafficmanagementsystemsinaccuratelypredictingandmanaging traffic conditions.

2.2 References

1. Li,W.,&Wang,D.(Year)."MachineLearningApproachesforTrafficVolumeEstimation:A Comprehensive Review." Journal of Transportation Engineering, Volume(Issue), Page Range.

2.Smith,J.,&Johnson,M.(Year).UrbanTraficManagement:ChallengesandOpportunities. Publisher:CityPress.

3. Zhang,Q.,etal.(Year)."Real-timeTrafficFlowPredictionwithBigData:ADeepLearning Approach."IEEETransactionsonIntelligentTransportationSystems,Volume(Issue),Page Range.

2.3 ProblemStatementDefinition

Urban areas worldwide are grappling with an escalating challenge in traffic managementsystems,markedbytheinadequacyoftraditionalapproachesto accuratelypredictandadapttodynamictrafficconditions.Existingsystems,relianton historical data and static algorithms, exhibit significant shortcomings, including inaccuratetrafficvolumepredictions,limitedreal-timeadaptabilitytosuddenchanges, and inefficient resource allocation. The fragmentation of traffic data from diverse sourcesfurtherimpedesthecreationofacomprehensiveandresponsivetrafficmodel. Consequently,thesedeficienciesleadtosuboptimaltrafficflow,increasedcongestion, environmental degradation, and compromised user experiences. Addressing these issues is imperative for the sustainable development of urban transportation systems. The"TrafficIntelligence-AdvancedTrafficVolumeEstimationusingMachineLearning" project is initiated to tackle these challenges by leveraging cutting-edge machine learning techniques to enhance the accuracy, real-time adaptability, and overall efficiencyoftraffic volumeestimationand management.

3.IDEATION&PROPOSEDSOLUTION

3.1 EmpathyMapCanvas

Anempathymapisasimple,easy-to-digestvisualthatcapturesknowledgeaboutauser's behaviours and attitudes.

Itisausefultooltohelpsteamsbetterunderstandtheirusers.

Creatinganeffectivesolutionrequiresunderstandingthetrueproblemandthepersonwho is experiencing it. The exercise of creating the map helps participants consider things from theuser’sperspectivealongwithhisorhergoalsand challenges.

Reference:https://www.mural.co/templates/empathy-map-canvas

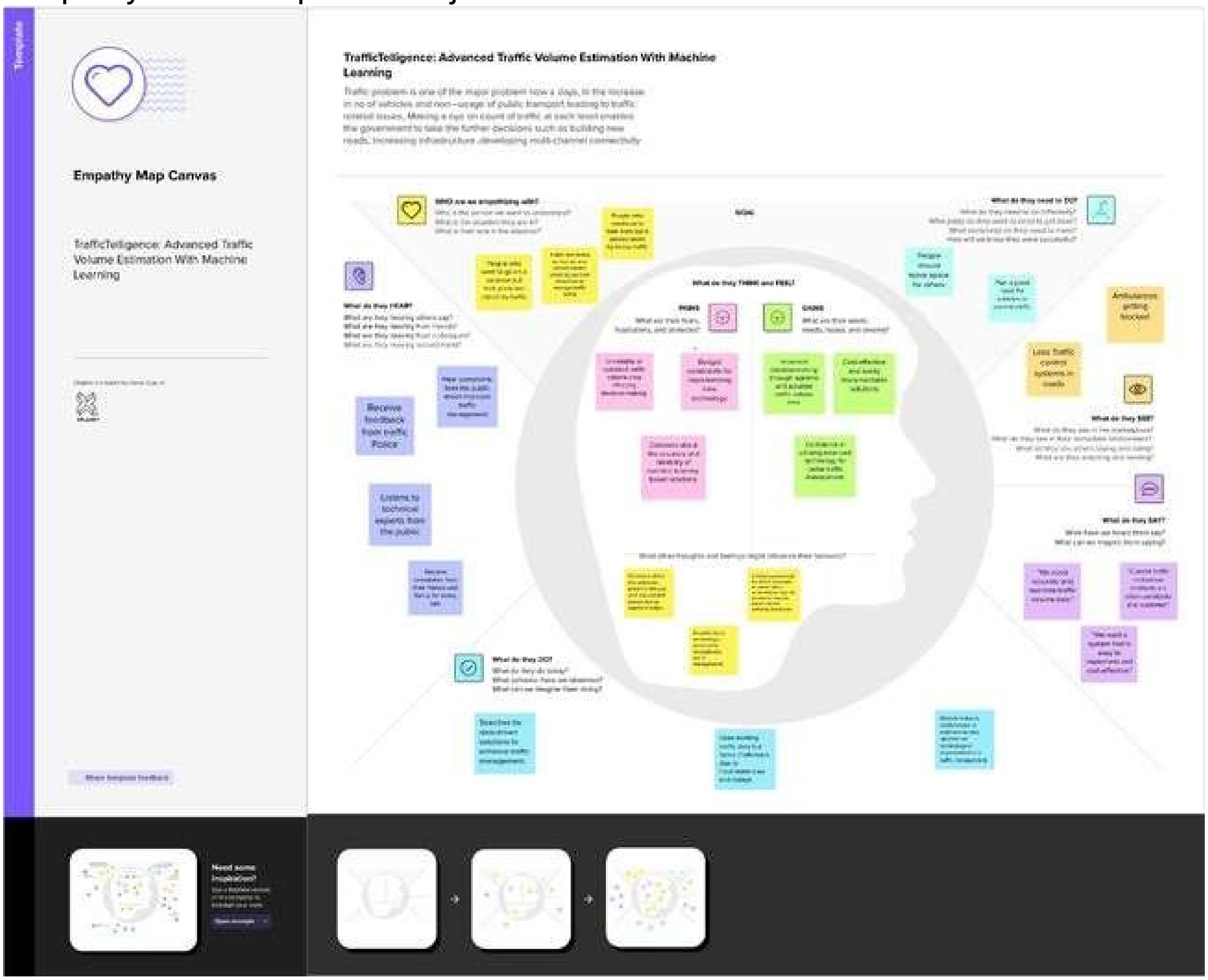
TrafficTelligence:AdvancedTrafficVolumeEstimationwithMachineLearning:

Trafficproblemisoneofthemajorproblemnowadays,Intheincreaseinnoofvehiclesand non–usageofpublictransportleadingtotrafficrelatedissues,Makingaeyeoncountoftraffic ateachlevelenablesthegovernmenttotakethefurtherdecisionssuchasbuildingnewroads, increasing infrastructure ,developingmutli-channel connectivity .

Toaddresssuchproblemstotrackingthevehiclecountineachandeveryplace AI-MLhasgiven asolutiontosuchkindoftrafficrelatedissues,whichareabletomeasurethevolumeoftraffic, identify the violations of traffic rules etc.ML models could give early alerts of severe traffic to
helppreventissuesrelatedtotrafficproblems.

Hence,thereisneedstodevelopMLalgorithmscapableinpredictingTrafficvolume with acceptablelevelofprecisionandinreducingtheerrorinthedatasetoftheprojectedTraffic volume from model with the expected observable Traffic volume.

EmpathyCanvasMapfortheProject:



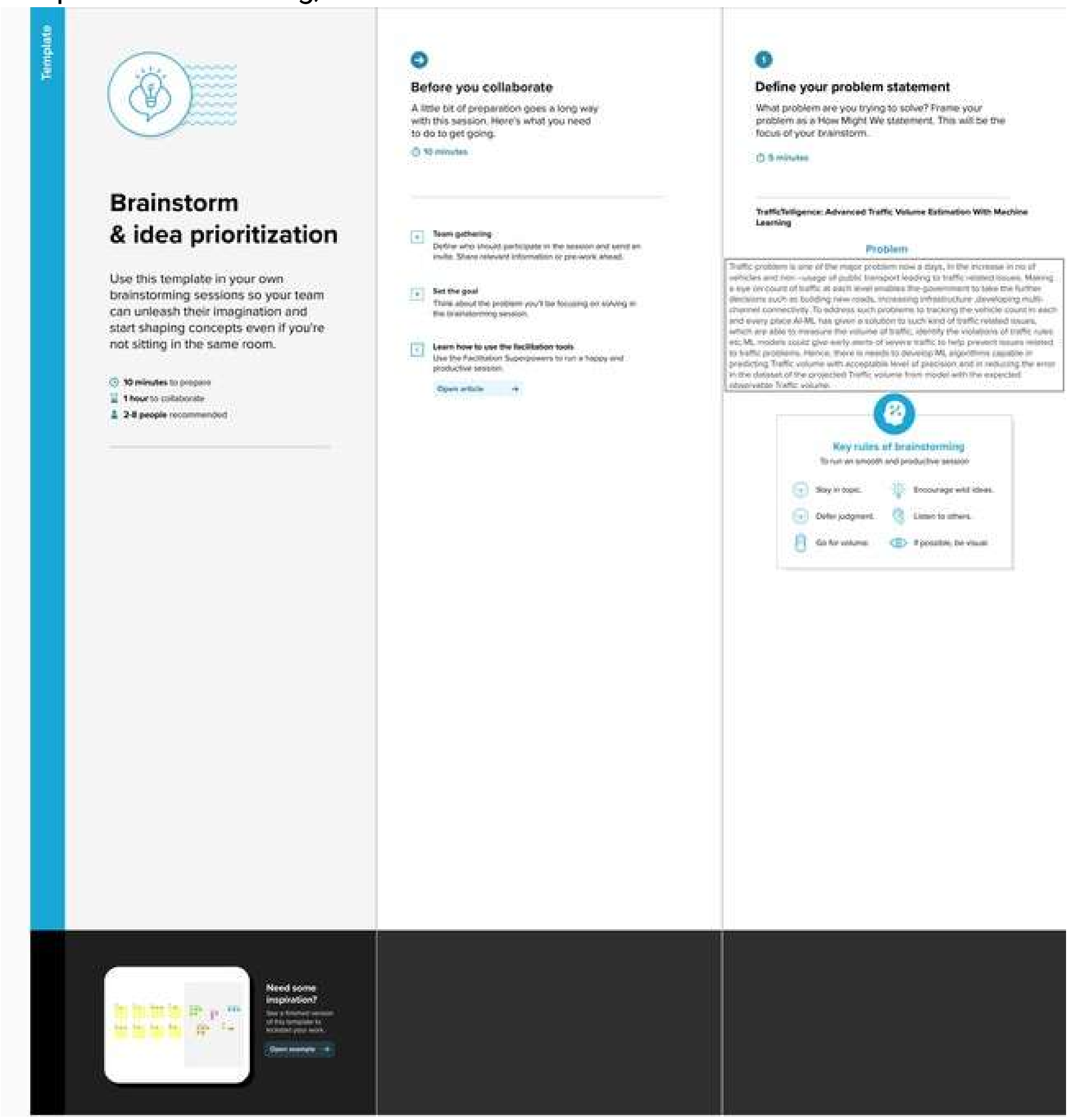
3.2 Ideation&Brainstorming

Brainstorming ideas is a creative process where a group generates a list of potential solutions, suggestions, or concepts for a specific problem or project. Voting in brainstorming involves participants selecting and prioritizing their favouriteormostpromisingideasfromthelisttodeterminewhichonesshould be pursued further.

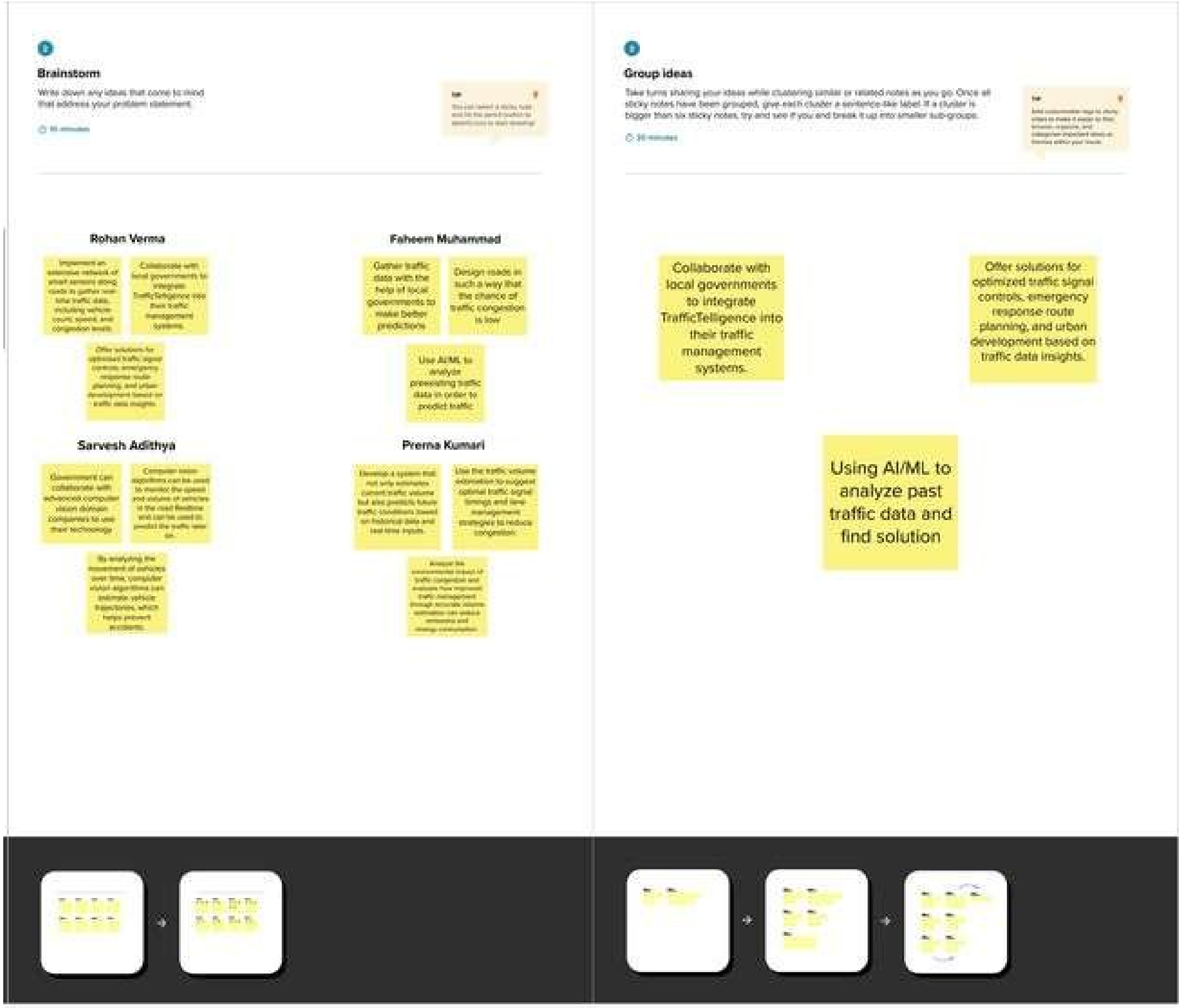
Brainstormingfor“TrafficTelligence:AdvancedTrafficVolumeEstimationwith Machine Learning”:

The objective of this brainstorming session is to generate creative and practical ideastoaddresstheissueofTrafficVolumeestimationeffectively.Weaimtohelp people able to plan their days better as they will have a better idea on how the traffic is going to be. It will also help traffic authorities be able to regulate traffic better.

Step-1:TeamGathering,CollaborationandSelecttheProblemStatement

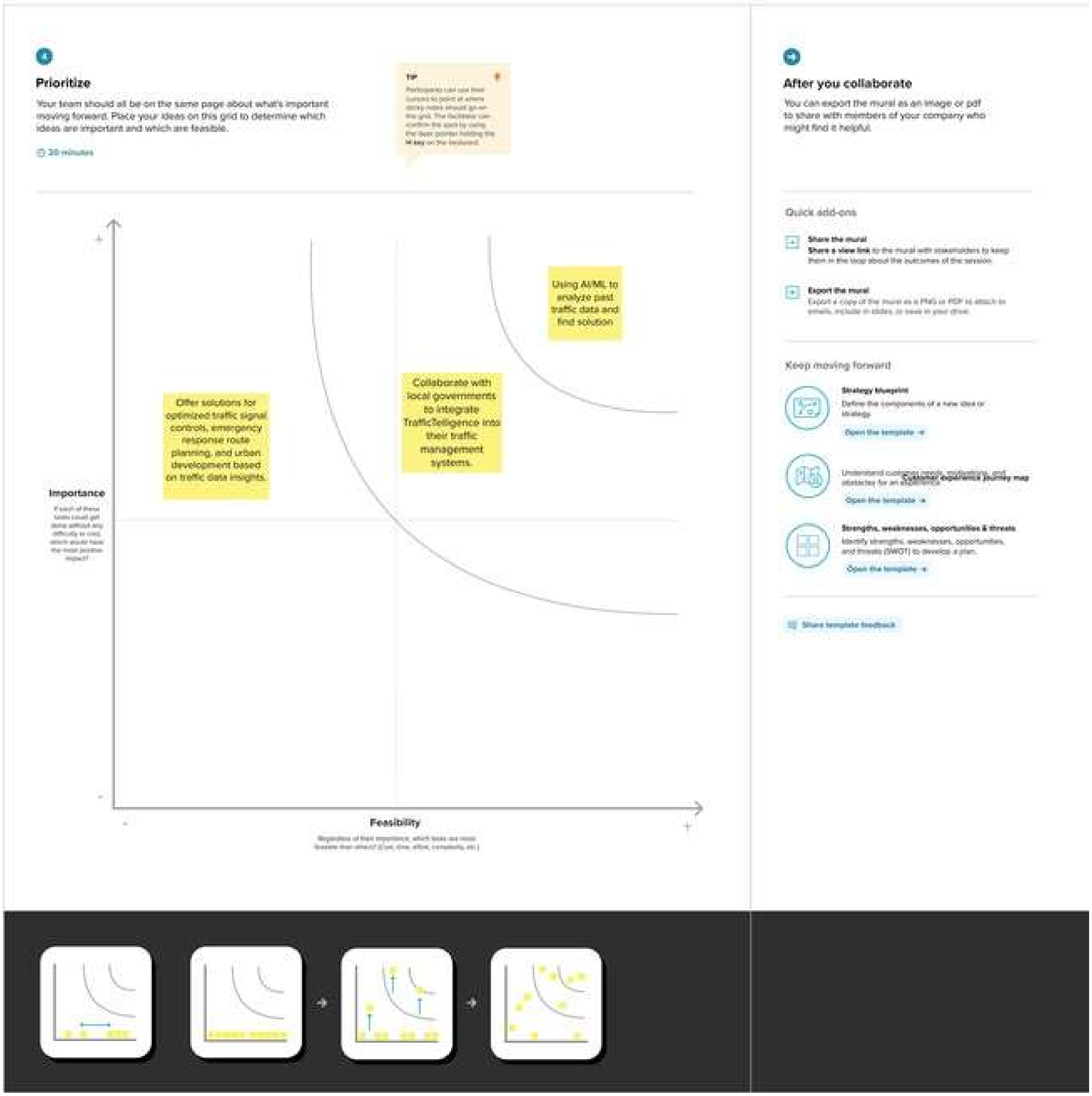


Step-2:Brainstorm,IdeaListingandgrouping



Step-3:IdeaPrioritization

Ideaprioritizationistheprocessofrankingorassessingideasbasedonspecific criteria such as feasibility, impact, cost, or strategic importance to determine which ideas should be implemented or pursued first.



Herecertainlywechose“UsingAI/MLtoanalyzepasttrafficdataandfind solution” is:

Among all of other ideas this was most important to us because, if the model is notaccurateenoughthenthepredictionmaynotbehighlyaccurate.So,thiswas our most prioritized one.

Then comes our second most important idea such as “Collaboration with local governmenttointegrateTrafficTelligenceintotheirtrafficmanagement systems”.Thiswastakenasoursecondbecause,ifwewanttogiveourselfasocial responsibility that will be helpful, not only to use but also for others. If we work with other government or organization this might be helpful for a smooth traffic without any problems for Traffic authorities and also for people.

Then comes out our next idea “Offer solutions for optimized traffic signal controls,emergencyresponserouteplanning,andurbandevelopmentbasedon trafficdatainsights.”Afterfulfillingourmaingoal,wewillscaleourMLmodelnot only to predict our main problem but also for extra features such as above-mentioned things. This will give our project more value in all ways.

4.REQUIREMENTANALYSIS

4.1 Functionalrequirement

Functionalrequirementsspecifythefundamentalactionsthatasystemmustperform.Forthe "Traffic Intelligence - Advanced Traffic Volume Estimation using Machine Learning" project, functional requirements might include:

1.DataCollection:

○Thesystemshouldcollectreal-timetrafficdatafromvarioussources,including cameras, sensors, and historical records.

○Itshouldensurethecontinuousandreliableacquisitionofdatafortrainingand updating the machine learning model.

2.FeatureEngineering:

○Thesystemmustidentifyandincorporaterelevantfeaturesfortrafficvolume estimation, such as time of day, weather conditions, and special events.

○Itshouldhavethecapabilitytoadaptandupdatefeaturesastrafficpatterns evolve.

3.MachineLearningModel:

○Developandimplementamachinelearningmodel(e.g.,neuralnetwork, regression models) for accurate traffic volume prediction.

○Themodelshouldbecapableofcontinuouslearningandadaptationtodynamic traffic conditions.

4.Real-TimeIntegration:

○Implementmechanismsforreal-timedataintegrationtoensurethemodelis continually updated with the latest traffic information.

○Thesystemshouldbecapableofhandlingandprocessinglargevolumesofreal- time data efficiently.

5.UserInterface:

○Developauser-friendlyinterfaceforstakeholderstovisualizetrafficdata, predictions, and insights.

○Theinterfaceshouldprovideinteractivefeaturesforexploringdifferent parameters and scenarios.

6.PredictionAccuracy:

○Defineperformancemetricsforthemachinelearningmodel,specifyingthe required level of accuracy for traffic volume predictions.

○Regularlyassessandimprovethemodel'saccuracythroughongoingmonitoring and updates.

7.AlertsandNotifications:

○Implementasystemforgeneratingalertsandnotificationsinreal-timefor abnormal traffic conditions or incidents.

8.Documentation:

○Providecomprehensivedocumentationforthesystem,includingdatasources, model architecture, and interface functionalities.

○Includeusermanualsandtechnicaldocumentationforfuturemaintenanceand updates.

4.2 Non-FunctionalRequirement

Non-functionalrequirementsdefinethequalitiesorattributesthatasystemmusthave,which are not directly related to specific behaviors or features. Here are some non-functional requirementsforthe"TrafficIntelligence-AdvancedTrafficVolumeEstimationusingMachine

Learning"project:

1.Performance:

○ResponseTime:Thesystemshouldprovidereal-timeornear-real-timeresponses to user queries and data updates.

○Throughput:Thesystemshouldhandleaspecifiednumberofrequestsper second to accommodate peak usage.

2.Reliability:

○Thesystemshouldhaveahighlevelofreliability,ensuringminimaldowntimefor maintenance and updates.

○ Itshouldrecovergracefullyfromsystemfailuresordisruptions.

3.Scalability:

○Thesystemshouldbescalabletoaccommodateanincreasingvolumeofdata and users as the project expands to cover additional regions.

○ Itshouldscalehorizontallybyaddingmorecomputationalresources.

4.Usability:

○Theuserinterfaceshouldbeintuitiveanduser-friendly,requiringminimaltraining for stakeholders to navigate and interpret data.

○ Thesystemshouldadheretoaccessibilitystandardstoensureinclusivity.

5.Security:

○DataEncryption:Allsensitivedata,includingtrafficdataanduserinformation, should be encrypted during transmission and storage.

○AccessControl:Thesystemshouldimplementaccesscontrolstorestrictdata access based on user roles and permissions.

6.Maintainability:

○Thesystemshouldbemodularandwell-documentedtofacilitateeaseof maintenance and updates.

○Codeshouldfollowbestpractices,andchangesshouldbedeployablewith minimal disruption.

7.Compatibility:

○Thesystemshouldbecompatiblewithcommonlyusedwebbrowsersand operating systems.

○Itshouldintegrateseamlesslywithexistingtrafficmanagementinfrastructure and systems.

8.PerformanceMonitoring:

○Implementasystemforcontinuousmonitoringofthemachinelearningmodel's performance, with alerts for deviations from expected behavior.

○ Logandmonitorsystemusageandperformancefortroubleshootingand optimization.

9.Privacy:

○Thesystemshouldcomplywithprivacyregulationsandguidelines,ensuringthat personally identifiable information is handled securely and responsibly.

○ Implementmechanismsforanonymizingandaggregatingdatawhereapplicable.

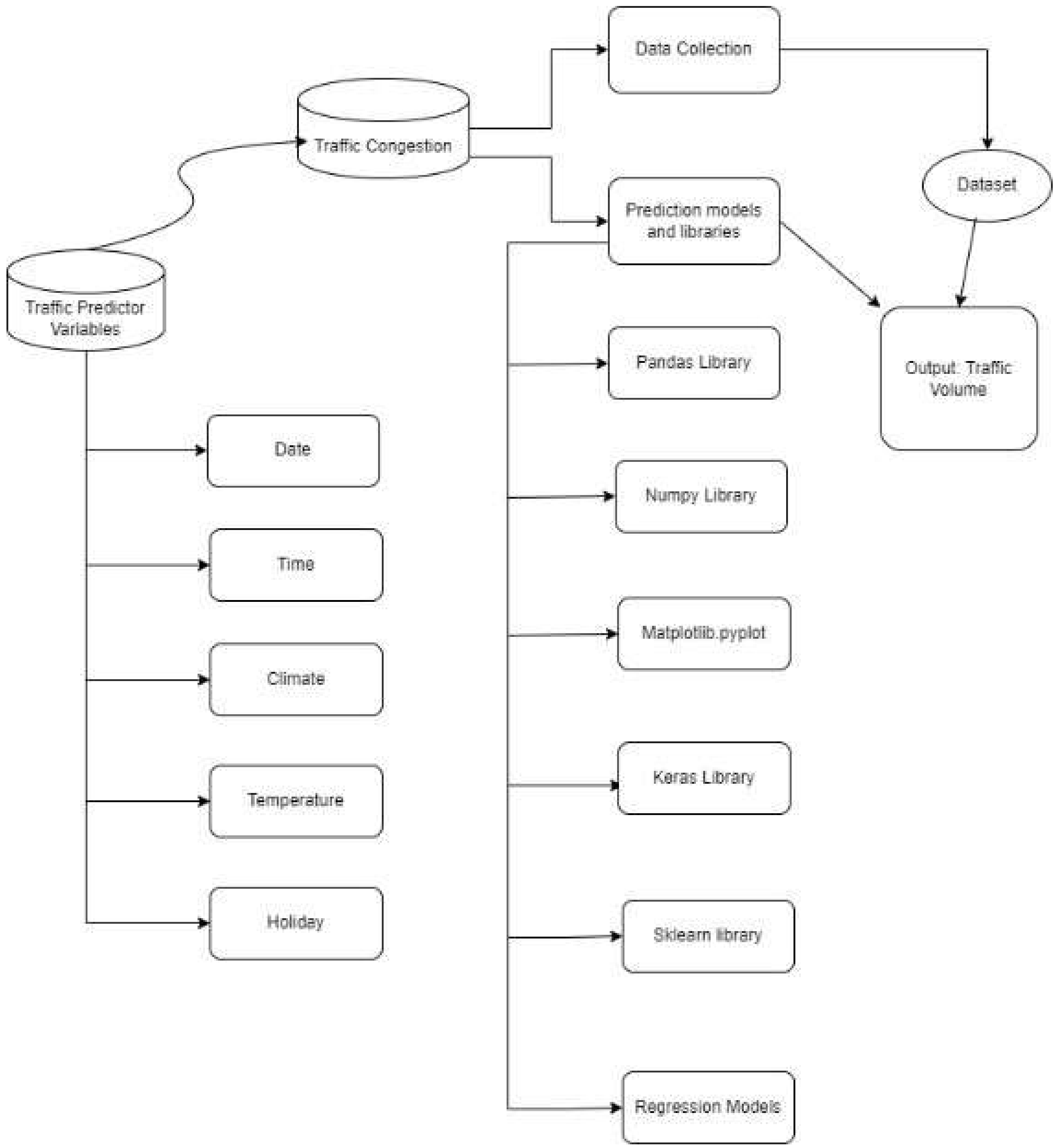
10. EnvironmentalConsiderations:

○Ifapplicable,considerenergy-efficientpracticesinsystemdesignandoperation to minimize environmental impact.

5.PROJECTDESIGN

5.1 Dataflowdiagram&UserStories

ADataFlowDiagram(DFD)isatraditionalvisualrepresentationoftheinformationflowswithina system.AneatandclearDFDcandepicttherightamountofthesystemrequirementgraphically.It shows how data enters and leaves the system, what changes the information, and where data is stored.



UserStories

UserType	Functional Requirement (Epic)	User Story Number	UserStory/ Task	Acceptance criteria	Priority	Release

TrafficManager	Real-time Traffic Estimation	USN-1	As a Traffic Manager,I want to access real-time traffic volume estimations to make informed decisions fortraffic control.	Systemprovides accurate real-time traffic volume predictions. Dataupdates occur at least every5minutes. Dataaccuracyis within a 95% confidence interval.	High	Sprint1
Driver	Real-time Traffic Estimation	USN-2	Application suggests a approximatecongestion in the route.	Application suggests an approximate congestionin the route.	High	Sprint1
Traffic Analyst	DataInsights on congestion volume	USN-3	As a Traffic Analyst, I wantaVolumenumber displaying in-depth traffic insights for informedanalysisand decision-making.	Volumenumber showcases traffictrends overvarious timeframes.	Medium	Sprint2
Website Developer	Model building	USN-4	AsanWebDeveloper, I want access to models that integrate TrafficTelligencedata forincorporationinto existing navigation applications.	Models provide accurate traffic data. Well-documented Models for easy integration. Allowsaccess to real-time andpredictive traffic estimations.	High	Sprint2

City Planner	Customizable TrafficSolutions	USN-5	AsaCityPlanner,I want customizable traffic solutions to accommodate specific citydevelopmentneeds.	Systemallows adjustmentsto traffic control strategies. Customization based on specific traffic conditions.	High	Sprint3
Educational Institutions	Training	USN-6	implementdata augmentationtechniques (e.g., rotation, flipping) to improve the model's robustnessandaccuracy.	wecould do testing	medium	Sprint4

	Testing&quality assurance	USN-7	conduct thorough testingofthe modeland webinterface to identify and report any issues or bugs. fine-tunethe model hyperparametersand optimizeitsperformance based on user feedback and testing results.	wecouldcreate web application	medium	Sprint5

5.2 SolutionArchitecture

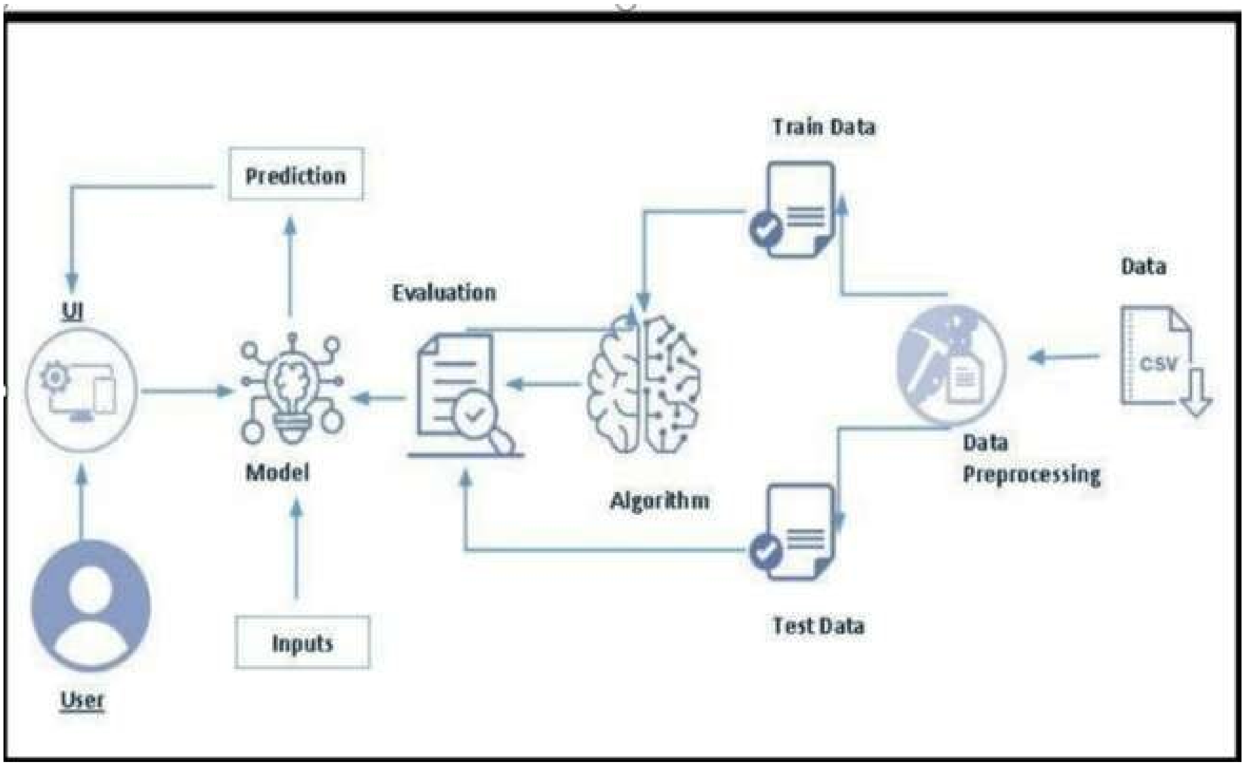
Traffic Intelligence: Advanced Volume Estimation Using Machine Learning" aims to enhance traffic volumeestimationforurbanplanningandmanagement.Bycollectingdiversetrafficdataandapplying machine learning, the project seeks to provide real-time, accurate traffic volume predictions, historical analysis, and anomaly detection, ultimately contributing to more efficient and informed traffic management.

OursolutionusesmanyadvancedMachinelearningAlgorithmstoaddresstheTrafficVolumeEstimation problem effectively.

Stepstobefollowed:-

1. DataCollection:Sensors,cameras,andIoTdevicescapturereal-timetrafficdata.
2. DataPre-processing:Cleanandpreprocessdatatomakeaneffectivemodel.
3. TrainModel:Usingpreprocesseddatatomakepredictivemodelsforforecastingtrafficvolume patterns for real-time estimations.
4. TestModel:Tomakesurethatthemodelisaccurateandefficient.
5. IntegratingModel:Tomakeauserfacingapplicationssothattheusercaninteractwiththe model.

SolutionArchitectureDiagram



6.PROJECTPLANNING&SCHEDULING

6.1 TechnicalArchitecture

TheDeliverableshallincludethearchitecturaldiagramasbelowandtheinformationasperthetable1& table 2

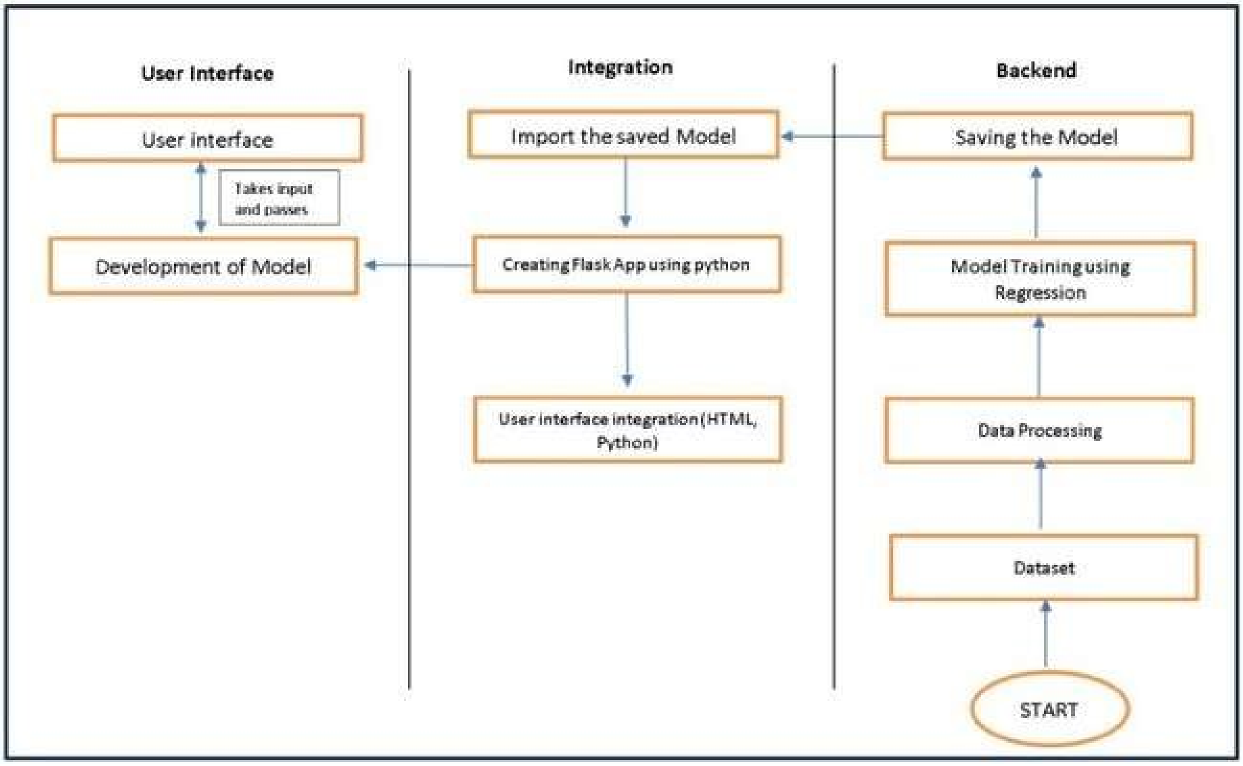


Table-1:Components&Technologies:

S.No	Component	Description	Technology
1.	UserInterface	Criticalelementdesigned forbothTrafficManagers and everyday users, ensuring an intuitive and informativeexperience.	HTML,CSS,JavaScript
2.	ApplicationLogic-1	Involvesarobustbackendsystem responsible for processing, analyzing,andmanagingtrafficdata.	Python
3.	Database	Involvesthestorageand management of diverse trafficdataforanalysis.	FileManager,csv
4.	FileStorage/Data	Involvesmanagingdiversetypesof data, including raw traffic data, machine learning models, and configurationfiles.	LocalSystem,Google Drive

5.	FrameWork	Itisacrucialpartofourprogramas it is responsible for connecting the frontendwiththebackend.	PythonFlask
6.	MachineLearningModel	The machine learning model is responsibleforpredictingfuture outcomesbasedonavailabledata	Machinelearningmodel createdusingregression algorithms
7.	Infrastructure(Server/ Cloud)	Involves a combination of servers and cloud services to support the computationalandstorageneeds of theapplication.	Local

Table-2:ApplicationCharacteristics:

S.No	Characteristics	Description	Technology
1.	Open-SourceFrameworks	Open-source frameworks can acceleratedevelopmentandensure thereliabilityofTrafficTelligence, contributing to a more efficient andmaintainablesolution.	Python'sFlask

S.No	Characteristics	Description	Technology
2.	Scalability	Using cameras to collect data andtomakemodelsforspecific locations.	Computer vision, dynamicdatabases.
3.	Performance	Regular performance testing, monitoring, and optimization are integral components of the development and maintenance processes, ensuring that TrafficTelligence consistently deliverstimelyandefficienttraffic volumeestimations.	R squared, Root mean squarederror,RootMean Square deviation

4.	Availability	Websitecanbemadeavailableall time in a webserver. This makes the website running without any issues	HighspeedLinuxbased webservers.

6.2 SprintPlanning&Estimation

Sprint	Functional Requirement (Epic)	User Story Number	UserStory/Task	Story Points	Priority	Team Members
Sprint-1	Projectsetup& Infrastructure	USN-1	Setupthedevelopment environmentwiththe requiredtoolsand frameworkstostartthe project	1	High	Prerna Kumari
Sprint- 2	Datacollection	USN-2	Gatheradiversedataset of Date, time, holidays and climaticconditions.	2	High	Faheem Muhammad
Sprint- 2	datapreprocessing	USN-3	Preprocess the collected dataset by removing outliers and null values etc.Exploreandevaluate different deep learning architectures(e.g., Regressions) to select the most suitable model forthe project.	3	High	Faheem Muhammad
Sprint-3	modeldevelopment	USN-4	traintheselectedmachine learningmodelusingthe preprocessed datasetandmonitoritsperformance on the validationset.	4	High	SarveshAdithya
Sprint-3	Training	USN-5	Thedatasetwillbe trainedwithsuitable algorithmstoimprove therobustness and accuracy.	6	medium	RohanVerma
Sprint-4	model deployment& Integration	USN-6	deploythetrained machinelearningmodel asawebservicetomake itaccessibleforusers. Integratethemodel's APIintoauser-friendly webinterfaceforusers toinputvariablessuch	1	medium	Sarvesh Adithya

	asdate,time,holidays
	etcandreceivepredicte d

			volumeresults.			
Sprint- 5	Testing&quality assurance	USN-7	conductthoroughtesting of the model and web interface to identify and report any issues or bugs. fine-tune the model hyperparameters and optimize its performance based on user feedback and testingresults.	1	medium	RohanVerma

6.3 SprintDeliverySchedule

Sprint	Total Story Points	Duration	SprintStart Date	SprintEnd Date (Planned)	Story Points Completed(as on Planned EndDate)	SprintRelease Date (Actual)
Sprint-1	1	3Days	3Nov2023	6Nov2023	1	6Nov2023
Sprint-2	5	2Days	6Nov2023	8Nov2023	5	8Nov2023
Sprint-3	10	5Days	8Nov2023	13Nov2023	10	13Nov2023
Sprint-4	1	5Days	13Nov 2023	18Nov 2023	1	20Nov2023
Sprint-5	1	4Days	18Nov 2023	22Nov 2023	1	21Nov2023

7.CODING&SOLUTIONING

7.1 Feature1

Onekeyfeatureoftheadvancedtrafficvolumeestimationusingmachinelearning projectistheintegrationofreal-timetrafficdata.Thisfeatureinvolvesthecontinuous collectionandincorporationofup-to-the-minuteinformationfromvarioussources,such as traffic cameras, sensors, and GPS devices. The system dynamically adapts to changing traffic conditions, ensuring that the machine learning models are constantly updated with the latest information. This real-time integration enables the traffic management system to respond promptly to fluctuations in traffic volume, incidents, or events,providingaccurateandtimelypredictionsforeffectivetrafficcontrol.Thefeature not only enhances the system's responsiveness but also contributes to more proactive decision-making in optimizing traffic flow and preventing congestion.

7.2 Feature2

Feature2:Multi-ModalTrafficAnalysis

Another crucial feature of the advanced traffic volume estimation using machine learningprojectisitscapabilityformulti-modaltrafficanalysis.Thisfeatureextendsthe scopebeyondtraditionalroadtrafficandincorporatesdiversemodesoftransportation, such as pedestrians, cyclists, and public transit. The machine learning models are designedtoanalyzeandpredictthevolumeandpatternsofvarioustransportation modes within the urban environment. This inclusive approach provides a comprehensiveunderstandingofoverallurbanmobility,allowingfortheoptimizationof traffic flow across different modes. By considering the interactions between pedestrians, cyclists, and public transportation, the system can contribute to the development of integrated and sustainable transportation solutions for modern urban landscapes.Thisfeaturereflectsaforward-lookingperspectivethatacknowledgesthe diverse nature of transportation systems in smart cities.

8.PERFORMANCETESTING

8.1 PerformanceMetrices

RMSDvalueofthefollowingmodelsare:

1. LinearRegression:1838.3976719006828
2. Decision Tree :1097.460402156461
3. Random Forest :794.1141248467267
4. Support Vector Regression :1715.2770939066922
5. XGBoost:797.8443863964126

RMSDvalueforRandomforestisverylesswhencomparedwithothermodels,so saving the Random forest model and deploying it.

9.RESULTS

9.1 OutputScreenshots

```
#Model Building
from sklearn import linear_model
from sklearn import tree
from sklearn import ensemble
from sklearn import svm
import xgboost
```

```
lin_reg = linear_model.LinearRegression()
Dtree = tree.DecisionTreeRegressor()
Rand = ensemble.RandomForestRegressor()
svr = svm.SVR()
XGB = xgboost.XGBRegressor()
```

```
#Testing the model
#1.using R-squared_score
from sklearn.metrics import r2_score
p1 = lin_reg.predict(x_test)
print(r2_score(p1,y_test))
```

```
-5.399396398322183
```

```
p2 = Dtree.predict(x_test)
print(r2_score(p2,y_test))
```

```
0.6932439744468677
```

```
p3 = Rand.predict(x_test)
print(r2_score(p3,y_test))
```

```
0.8058847456428343
```

```
p4 = svr.predict(x_test)
print(r2_score(p4,y_test))
```

```
-11.972215715232434
```

```
p5 = XGB.predict(x_test)
print(r2_score(p5,y_test))
```

```
0.8066516776309793
```

```
#2. Using Ro
from sklear
```

```
MSE = metri
np.sqrt(MSE
```

```
1838.397671
```

In [71]:

```
fro
x_t
```

```
y = data['traffic_volume']
x = data.drop(columns=['traffic_volume','holiday','weather'],axis=1)
```

```
names = x.columns
```

```
from sklearn.preprocessing import scale
```

```
x = scale(x)
```

```
x = pd.DataFrame(x,columns=names)
```

```
x.head()
```

	temp	rain	snow	day	month	year	hours	minutes	seconds	weather_v2	holiday_v2
0	0.530485	-0.007463	-0.027235	-1.574903	1.02758	-1.855294	-0.345548	0.0	0.0	-0.566452	0.015856
1	0.611467	-0.007463	-0.027235	-1.574903	1.02758	-1.855294	-0.201459	0.0	0.0	-0.566452	0.015856
2	0.627964	-0.007463	-0.027235	-1.574903	1.02758	-1.855294	-0.057371	0.0	0.0	-0.566452	0.015856
3	0.669205	-0.007463	-0.027235	-1.574903	1.02758	-1.855294	0.086718	0.0	0.0	-0.566452	0.015856
4	0.744939	-0.007463	-0.027235	-1.574903	1.02758	-1.855294	0.230807	0.0	0.0	-0.566452	0.015856

```
#Model Depl
#saving the
import pick
from sklear
le = le = L
pickle.dump
pickle.dump
```

```
lin_reg.fit(
Dtree.fit(x_
Rand.fit(x_t
svr.fit(x_tr
XGB.fit(x_tr
```

```
XGBRegressor
```

```
#importin

import pa
import nu
import se
```

```
#importing
data = pd.r
```

In [4]:

Out[4]:

In [5]:
```
#used to display the basic information of the data

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48204 entries, 0 to 48203
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   holiday         48204 non-null  object
 1   temp            48151 non-null  float64
 2   rain            48202 non-null  float64
 3   snow            48192 non-null  float64
 4   weather         48155 non-null  object
 5   date            48204 non-null  object
 6   Time            48204 non-null  object
 7   traffic_volume  48204 non-null  int64
dtypes: float64(3), int64(1), object(4)
memory usage: 2.9+ MB
```

In [6]:
```
# used to display the null values of the data

data.isnull().sum()
```

Out[6]:
```
holiday            0
temp              53
rain               2
snow              12
weather           49
date               0
Time               0
traffic_volume     0
dtype: int64
```

In [14]:
```
data['temp'].fillna(data['temp'].mean(),inplace=True)
data['rain'].fillna(data['rain'].mean(),inplace=True)
data['snow'].fillna(data['snow'].mean(),inplace=True)

print(Counter(data['weather']))
```

```
Counter({'Clouds': 15144, 'Clear': 13383, 'Mist': 5942, 'Rain': 5665, 'Snow': 2875, 'Drizzle': 1818, 'Haze': 1359, 'Thunderstor
m': 1033, 'Fog': 912, nan: 49, 'Smoke': 20, 'Squall': 4})
```

In [15]:
```
data['weather'].fillna('Clouds',inplace=True)
```

In [15]:
```
data['weather'].fillna('Clouds',inplace=True)
```

In [17]:
```
#splitting the date column into year,month,day
data[["day", "month", "year"]] = data["date"].str.split("-", expand = True)
```

In [18]:
```
#splitting the Time column into hour,minute,second
data[["hours", "minutes", "seconds"]] = data["Time"].str.split(":", expand = True)
```

In [19]:
```
data.drop(columns=['date','Time'],axis=1,inplace=True)
```

In [20]:
```
data.head()
```

Out[20]:

	holiday	temp	rain	snow	weather	traffic_volume	day	month	year	hours	minutes	seconds
0	None	288.28	0.0	0.0	Clouds	5545	02	10	2012	09	00	00
1	None	289.36	0.0	0.0	Clouds	4516	02	10	2012	10	00	00
2	None	289.58	0.0	0.0	Clouds	4767	02	10	2012	11	00	00
3	None	290.13	0.0	0.0	Clouds	5026	02	10	2012	12	00	00
4	None	291.14	0.0	0.0	Clouds	4918	02	10	2012	13	00	00

In [21]:
```
#used to understand the descriptive analysis of the data
data.describe()
```

Out[21]:

	temp	rain	snow	traffic_volume
count	48204.000000	48204.000000	48204.000000	48204.000000
mean	281.205351	0.334278	0.000222	3259.818355
std	13.336338	44.789133	0.008168	1986.860670
min	0.000000	0.000000	0.000000	0.000000
25%	272.180000	0.000000	0.000000	1193.000000
50%	282.429000	0.000000	0.000000	3380.000000
75%	291.800000	0.000000	0.000000	4933.000000
max	310.070000	9831.300000	0.510000	7280.000000

In [27]:
```python
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows
# how to understand word labels.
label_encoder = preprocessing.LabelEncoder()
```

In [30]:
```python
 data['weather']= label_encoder.fit_transform(data['weather'])
data['holiday'] = label_encoder.fit_transform(data['holiday'])
```

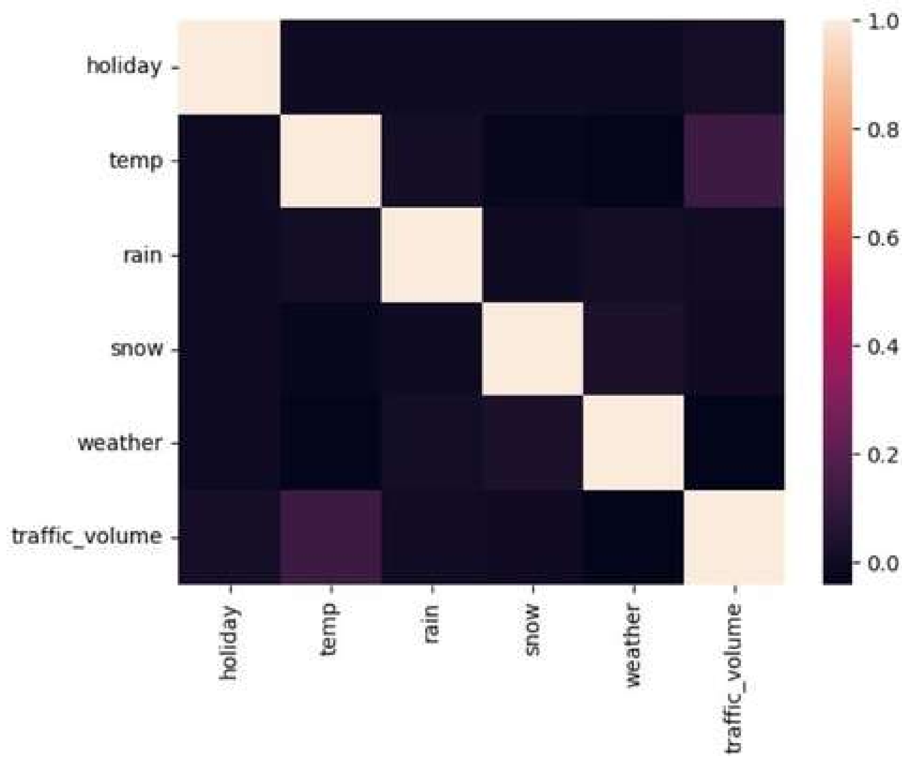
In [32]:
```python
cor = data.corr()
cor
```

Out[32]:

	holiday	temp	rain	snow	weather	traffic_volume
holiday	1.000000	-0.000472	0.000066	0.000432	-0.004328	0.018676
temp	-0.000472	1.000000	0.009070	-0.019758	-0.033559	0.130034
rain	0.000066	0.009070	1.000000	-0.000090	0.009542	0.004714
snow	0.000432	-0.019758	-0.000090	1.000000	0.036662	0.000735
weather	-0.004328	-0.033559	0.009542	0.036662	1.000000	-0.040035
traffic_volume	0.018676	0.130034	0.004714	0.000735	-0.040035	1.000000

In [33]:
```python
sns.heatmap(cor)
```

Out[33]: <AxesSubplot:>



In [52]:

```
sns.
```

```
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ons1
sul
  wa
```

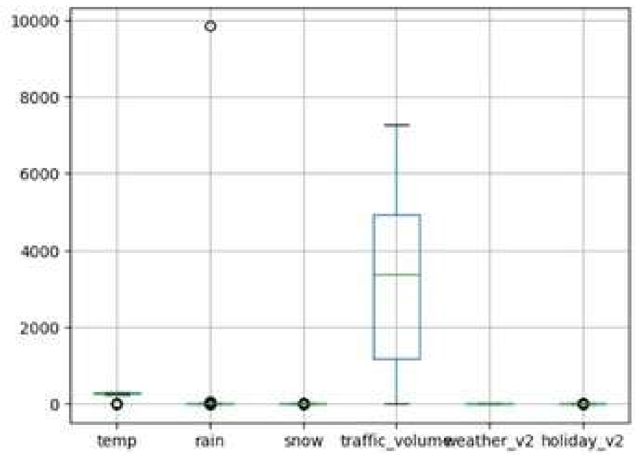
Out[52]:

```
<axe
```

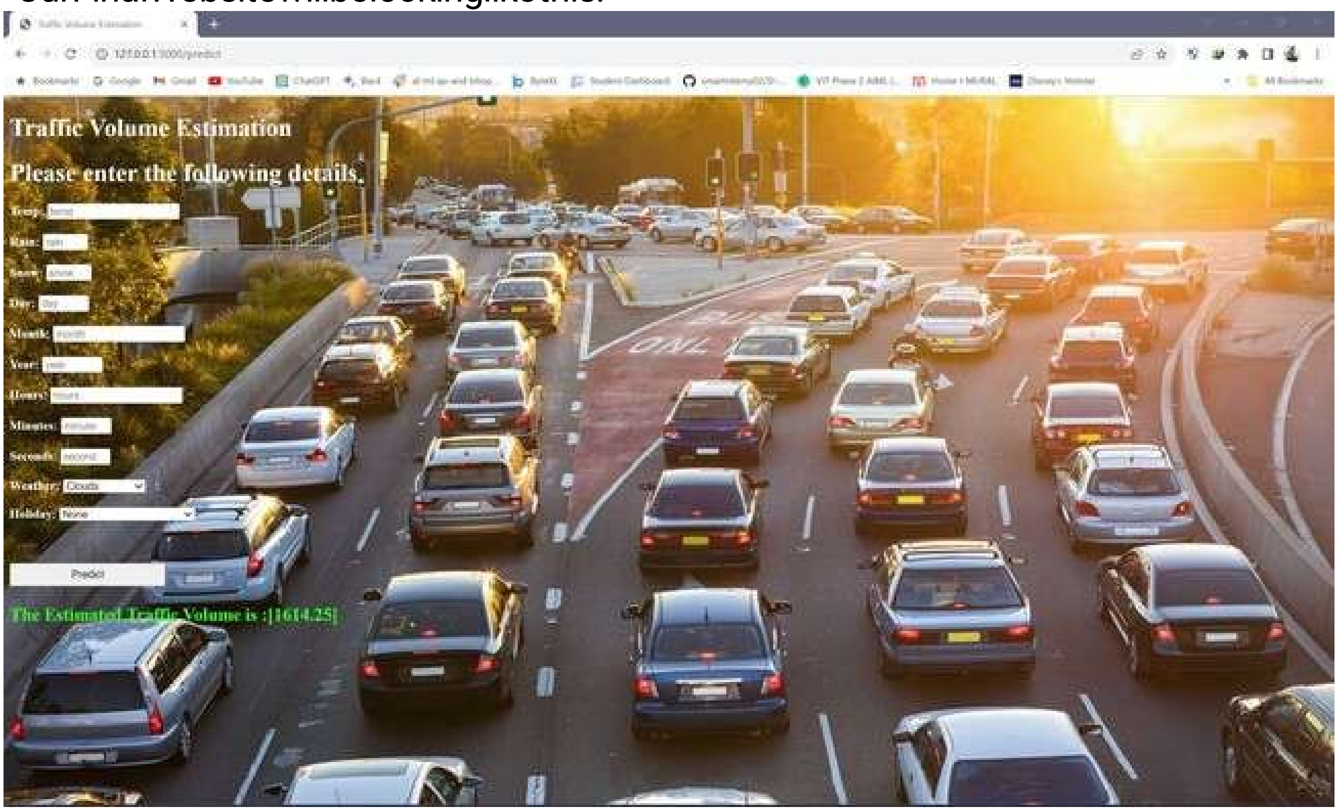
```
In [57]: sns.c
         plt.s
```

```
D:\An
ersio
sul
    war
```

```
In [59]: data.boxplot()
Out[59]: <AxesSubplot:>
```



OurFinalWebsitewillbelookinglikethis:



10. ADVANTAGES&DISADVANTAGES

Advantages:

1.Improved Accuracy:

○Machinelearningmodelscananalyzelargedatasetsandidentifycomplex patterns that may be challenging for traditional methods. This leads to moreaccuratetrafficvolumepredictions.

2.IntegrationwithSensorData:

○ Machinelearningmodelscaneffectivelyintegratedatafromvarious sources,suchastrafficcameras,sensors,andGPSdevices,providinga comprehensive view of the traffic situation.

3.Scalability:

○Machine learning algorithms can scale to handle large and complex datasets,makingthemsuitableforcitieswithextensivetrafficnetworks.

4.PredictiveCapabilities:

○Machinelearningmodelscanbeusedtopredictfuturetrafficconditions based on historical data, helping authorities proactively manage traffic flow and prevent congestion.

Disadvantages:

1.DataDependency:

○Machine learning models heavily rely on high-quality and representative data.Ifthetrainingdataisbiasedorincomplete,themodel'spredictions may be inaccurate or skewed.

2.Complexity:

○ Buildingandmaintainingmachinelearningmodelscanbecomplexand requirespecializedknowledge.Thiscomplexitycanhindertheadoptionof these systems, especially for smaller municipalities with limited resources.

3.DynamicNatureofTraffic:

○Trafficpatternsareinfluencedbyawiderangeoffactors,andtheycan changerapidly.Machinelearningmodelsmaystruggletokeepupwith these dynamic changes, especially if not continuously updated and retrained.

11. CONCLUSION

Inconclusion,theapplicationofmachinelearningforadvancedtrafficvolume estimationintherealmoftrafficintelligencebringsforthasetofnotableadvantages and challenges. The accuracy and adaptability offered by machine learning models present a promising avenue for enhancing traffic management. Real-time analysis capabilities,integrationwithdiversedatasources,scalability,andpredictivecapabilities contribute to more efficient and proactive traffic control.

However,thesuccessfulimplementationofmachinelearninginthiscontextrequires addressing several challenges. The dependency on high-quality and unbiased data, the inherent complexity of building and maintaining these models, and the interpretability issues associated with certain algorithms pose significant hurdles. Additionally, the dynamicnatureoftrafficpatternsandthecomputationalresourcesrequiredfortraining and running sophisticated models underscore the need for careful consideration and resourceallocation.

12. FUTURESCOPE

In the future, the application of advanced traffic volume estimation using machine learningholdstremendouspromiseinreshapingurbanmobilityandtransportation systems.Ongoingresearcheffortsarelikelytofocusonenhancingpredictionaccuracy through the exploration of sophisticated algorithms, feature engineering techniques, andensemblemethods.Asignificantavenuefordevelopmentliesintheintegrationof traffic intelligence with broader smart city initiatives, facilitating interconnected urban transportation systems that optimize traffic flow and minimize environmental impact. The adoption of edge computing is poised to enable real-time analysis at the source, reducing latency and enhancing responsiveness. Overcoming the interpretability challenge by incorporating explainable AI techniques will be crucial for building trust amongcityplannersandthepublic.Futuresystemsmayextendbeyondroadtrafficto encompassmulti-modaltransportation,incorporatingpedestrians,cyclists,andpublic transit.Thedynamicadaptationofmachinelearningmodelstounforeseeneventsand continuousimprovementmechanismsthroughonlinelearningandfeedbackloopsare vital considerations. Collaborative efforts between municipalities, transportation agencies, and technology providers can lead to more comprehensive and effective trafficmanagementsolutions,fosteringaconnectedandefficienttransportation network.Ultimately,thefutureofmachinelearningintrafficintelligenceliesinitsability to create sustainable, adaptive, and energy-efficient urban mobility solutions.

13. APPENDIX

OurCompleteSourceCode

1. ModelPython