European Journal of Molecular &Clinical Medicine,7(4):

Research Article

# Surveillance of Road Traffic by Predicting the Rapidity using ITS System

**Anjani Rai, Ashish Sharma,**

**Anjani Rai, Ashish Sharma**,
Department of Computer Engineering,
GLA UNIVERSITY, MATHURA.
Ashish Sharma, Department of Computer Engineering,
GLA UNIVERSITY, MATHURA. E-Mail: anjani.rai@gla.ac.in

**ABSTRACT**

Road traffic rapidity forecasting may be a testing problem done intelligent transport system (ITS) and need picked up expanding attentions. Existing meets expectations would principally In light of crude rapidity sensing data gotten from framework sensors or explored vehicles that are restricted Toward unreasonable cosset for sensor sending And upkeep. With meagre pace observations, accepted routines depended main on pace sensing data need aid insufficient, particularly the point when emergencies such as traffic mishaps happen. On location the problem, this paper plans on enhance those way traffic rapidity forecasting Toward fusing universal pace sensing data for new-type “sensing” data from cross area sources, for example, tweet sensors from Online networking and path sensors from guide And traffic administration platforms. Mutually displaying majority of the data starting with different datasets acquires huge numbers challenges, including area questionable matter of low-determination data, dialect vagueness of traffic portrayal in writings Also heterogeneity of cross-domain data. Because of the opposition on this disputes, we exhibit a bound together probabilistic system, known as Topic-Enhanced Gaussian procedure amassed representation (TEGPAM), comprising about apparatus, i. E. Area disaggregation representation, traffic subject representation Also traffic rapidity Gaussian transform representation, that coordinate new-type data with customary data. Investigations looking into true data from two expansive urban areas On America accept the adequacy and effectiveness by our representation.

Keywords ITS system, Road traffic, Sensors



## Introduction:

### Background and inspiration

Road traffic surveillance is of incredible significance for urban transport framework. Activity manage organizations And drivers Might profit starting with auspicious And exact way traffic forecasting And make punctual, or considerably propel choices conceivable to identifying and keep away from road blocking. Present systems basically concentrate on crude pace sensing data gathered starting with cameras alternately road sensors, And endure extreme data shortage problem Since those establishment And upkeep of sensors are thick, as exorbitant [56]. In the same time, practically existing strategies depended just ahead secret word Also present traffic states (e. G [9], [54], [25], [38]) don't fit great The point when real-world variables for example, such that traffic mishaps assume a a piece.

On location the over problems, present paper we present new-type traffic associated data emerging as of government funded services: 1) Online networking data, that is presented looking into informal communication websites, e. G. Twitter and Face book. With those popularization for portable strategies persons would less averse to trade news And trifles On their an aggregation through Online networking services, the place messages regarding traffic conditions, for example, “Stuck over traffic once e 32nd St. Remain away!”, would presented Toward drivers, Travellers and pedestrians who can be seen as sensors watching those progressing traffic states close their physical areas. In traffic powers record open financial statement and post tweets with advise people in general of the traffic status, such.

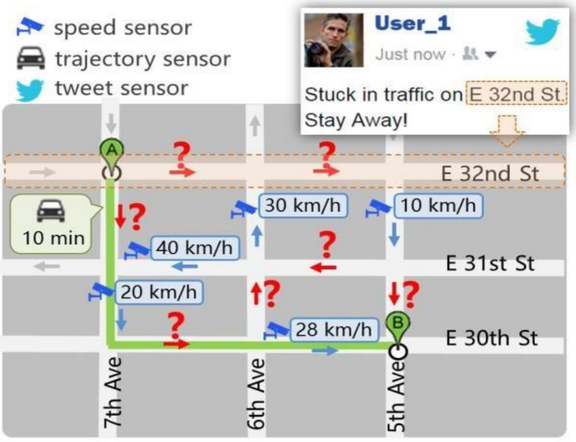



Fig. 1: problem setting. Our objective will be with anticipate those traffic rapidity for particular road links, Likewise indicated for the red inquiry marks, specified: 1) some rapidity perceptions gathered By rapidity sensors, as demonstrated by blue; 2) path And travel time by odd pairs reminder that rapidity for passed road joins are possibly watched alternately on a chance to be forecasted; 3) tweets describing traffic states. Note that that area said by a tweet might make a road coating different road joins. Likewise “Slow traffic around I95 sb from Girard Ave on Vine St.” presented toward neighbourhood transport department account. Such content communication recounting traffic states And A percentage of

them labelled with area data would receptive By government funded and Might make a integral majority of the data hotspot of crude rapidity sensing data [8].

(OD) couple for a map, such administrations could propose ideal course starting with those root of the end with minimum time, Also trajectories could a chance to be gathered when drivers utilize the administration will explore [9]. Here a path may be an arrangement about joins for An provided for odd pair, Also a join is An way section between neighbouring intersections. Consequently, a path travel time will be an joining about join travel times, that are identified with the real-time way traffic rapidity. Longer path travel time demonstrates that a few directing, including road joins might a chance to be congested with more level traffic pace. Path data will be handy to an extensive variety about transport analyses and requisitions [49] [9].

In light of those over observations, the place customary traffic sensing data need aid set same time new-type data starting with Online networking and guide administration start will spring up, our objective is should foresee those road-level traffic pace Toward integrating new type data for customary rapidity sensing data [10]. Should rouse this scenario, Think as of a road traffic forecasting sample delineate over fig. 1. The individuals joins over red address marks would not secured By customary rapidity sensors, in any case might a chance to be approved Toward trajectories appended with travel time data, alternately specified Previously

**Challenges:**

When coordination accepted traffic pace data with foresee way traffic rapidity, specialized foul tests emerge because of those trademark by each data source:.

**Area vulnerability about low-determination data;** tweet data and path data need aid known as low-determination data on we can't straightforwardly find them under particular road joins. Practically tweets bring no area tags; thereabouts geographic area dialect may be that fundamental clue, that Nonetheless morals are ambiguous [11]. For example, outflow similar to stuck in traffic a head e 32nd St. Remain away! Blankets the entirety road with no exact way areas In journey time of a path may be an aggravator calculate dependent upon the rapidity about different links, that might differ generally. Accordingly a system may be obliged on disaggregate those data will particular road links;.
Dialect uncertainty by traffic depiction over tweets; the expressions portraying traffic states would diverse, Also might mean different rapidity qualities. A sample will be demonstrated in fig. 2, that indicates the recurrence circulation in that level of blockage At individuals utilization congestion-related expressions. Then some expressions not specifically identified with traffic might additionally have solid suggestion with join rapidity, for example, expressions whining awful climate. Accordingly a semantic representation is obliged will catch those examples the middle of discrete spellbinding expressions Also constant pace standards [12].

Heterogeneity for multi-source data; those data sources have dissimilar assets and idle family for the road traffic rapidity like tweets have idle topics that group In view of rapidity levels, And negative correspondence existed the middle of path travel time And traffic rapidity of directing, including joins. In this way an bound together schema will be required on representation these properties And aggravator the idle relations the middle of heterogeneous data will anticipate rapidity unnaturally.

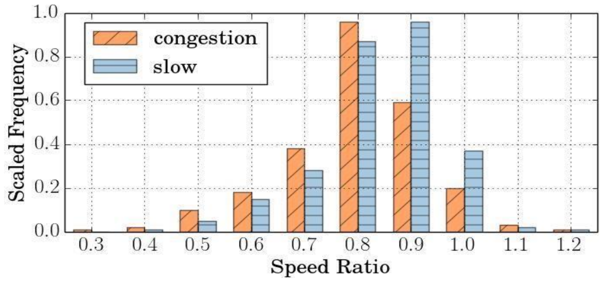



Fig. 2: The allocation of word frequencies while individuals apply writing “congestion” and “slow” to explain traffic, regarding the ratio among present rapidness and a suggested rapidness, that is clear by INRIX as the “uncongested free flow rapidity” for every road section. X-axis signifies the rapidness ratio and Y-axis signifies the rate of recurrence scale regarding the major assessment.

**Assistance**

Despite the great possibility by these new-type data, of the best for our information, those crisis by road-level traffic pace forecasting utilizing various data sources need not been great investigated before, particularly for the previously stated tests. present paper, we recommend a bound together measurable system, permitted theme improved Gaussian procedure amassed representation (TEGPAM) fusing multi-source data, that incorporates universal rapidity sensing data, And new-type “sensing” data from Online networking And map benefits. The skeleton unites those area disaggregation representation to break down ambiguous areas under particular links, the traffic theme representation with handle those dialect vagueness over tweets and the Gaussian transform representation should catch those spatial correspondence in traffic sensing data.

Particularly, this paper creates the taking after assistance:.
Coordination of data starting with different cross-domain sources. We actualize all the clue about moving forward traffic pace forecasting By coordination pace sensing data for new-type traffic-related data, for example, tweet Also path.

Detailing of the bound together TEGPAM schema. We suggest An bound together probabilistic skeleton TEGPAM that unites the disaggregation representation, subject representation with Gaussian transform representation And is gained By dissimilarity strategies And An stochastic EM calculation.
Far reaching trials on accept those execution of the suggested system. We accept our methodology utilizing real-world data gathered from two huge American urban communities. The far reaching examinations demonstrate that energy of TEGPAM, and in addition those representation effectiveness also unwavering quality.

Involved analyses by acquainted traffic-related data. We investigate the effects for diverse data sources, by disintegrating TEGPAM under sub representations and evolving the blending proportion about datasets. Similar examinations exhibit those energy of every data source.

Whatever remains of this paper will be sorted out as takes after. Segment 2 reviews related meets expectations. Segment 3 provides for a preliminary on Gaussian procedure. Segment 4 characterizes the problem and displays the representation configuration. Segment 5 provides for representation induction. Area 6 analyzes those effects of analyses on true data. Segment 7 finishes up those paper And proposes future instructions.

## RELATED WORKS

Traffic forecasting problem could be comprehensively ordered under transient And long haul forecasting [1], acknowledging three principle essential traffic measurements: traffic flow, an equal stream rate to vehicles; rapidity, imply of the watched vehicle rapidity; path habitation, those rate of chance that the sensor will be identifying vehicle vicinity. This paper keeps tabs on the short-term traffic pace forecasting joining multisource heterogeneous data, that, Likewise a long way as we know, need not been great investigated in front of. This part provides for a outline ahead transient traffic rapidity forecasting and the investigation for fusing different majority of the data sources.

Fleeting traffic rapidity Forecasting: the accessible techniques could be ordered under two category:

1) Parametric methods, expect that traffic rapidity follows a likelihood appropriation dependent upon an altered situated about parameters. Time arrangement dissection method will be connected over traffic pace forecasting dependent upon those periodicity of traffic pace throughout An day or a week. Auto-Regressive moving Normal (ARMA) representations need aid embraced to [46] and [38], the place Multivariate Spatial-Temporal Auto-Regressive (MSTAR) representation may be embraced will incorporate reliance Around perceptions from neighbouring areas. A survey something like Auto-Regressive coordinated moving Normal (ARIMA) time arrangement strategies could a chance to be discovered On [55]. ARIMA Also Winters exponential smoothing strategies need aid used to conjecture urban turnpike stream over [54]. [53] Differentiate ARIMA representations for An set for circle detectors that fuse data from upstream estimation areas. A absolute space-time Auto-Regressive incorporated moving Normal (STARIMA) representation may be recommended will depict the spatiotemporal advancement about traffic stream On an urban organize Previously, [26], that may be basically a compelled vector Autoregressive moving Normal (VARIMA) representation [13] with imperatives organize And bring about An intense diminishment in the amount of parameters. An summed up space-time ARIMA (GSTARIMA) technique will be suggested by [57], that extends ARIMA done spatial And fleeting extent And is that's only the tip of the iceberg adaptable Since parameters need aid outlined will differ for every special area. Kalman filter-depended methodologies are utilized within [11] And [14], And demonstrate points of interest for on-line estimation of traffic streams. Markov rationale system is utilized to all the while foresee that blockage state to [30]. An organized time arrangement representation may be recommended for multivariate type for fleeting traffic forecasting by [12].

2) Non-parametric methods make no appropriation presumptions and the number of parameters scales for that amount about preparation data. K-nearest neighbour (KNN) nonparametric relapse methods, e. G. [9], [21], [58], find that k nearest neighbours utilizing Euclidean separation and ascertain that weight. Unbiased Networks (NNs), e. G. [50], [27], need aid biologically inspired frameworks And might a chance to be prepared should estimated essentially any nonlinear work provided for sufficient data and An best possible system structural engineering. NNs need significant number subsidiaries to short-term forecasting, for example, such that go proliferation unbiased organize for hereditary calculations [1] Also wavelet networks [22]. Head out rapidity by each road fragment is registered utilizing those GPS trajectories By An context-aware grid factorization methodology by [45]. Should adaptively course An armada about helpful vehicles under those questionable And changing road blockage states by [33] and [34], An GP probabilistic representation will be recommended will catch those spatial and transient connections about head out rapidity In road segments and transient contexts, particularly for estimating those intend And covariance of the GP former starting with the authentic data. Geo statistical insertion strategies named Kriging are suggested will catch spatial and fleeting evolutions by traffic streams over [48].

Traffic demonstrating for Multi-Source heterogeneous Data:. A portion specialists endeavoured to consolidate traffic sensing data with other data sources, will handle outside Components for example, traffic mishaps (e. G. [36], [42]), versatile sensors (e. G. [39], [40]) and climate (e. G. [37], [2]). [37] reconsider those writing on the sway by climate ahead traffic stipulate, traffic security, And traffic stream associations. An path-depended Group disclosure system is suggested by [32], the place the path comparability will be demonstrated by a few sorts about kernels for distinctive data indicator (e. G. Semantic belongings of the areas and the development rapidity). [29] Tackles those rents/returns bicycle amount forecasting problem utilizing different characteristics, e. G. Period Also meteorology, similarly as instrument of similitude capacities by multi-similarity-depended induction representation. Same time [32] Also [29] present separate majority of the data sources By novel description for registering the comparison, our fill in accepts the idle relations the middle of these dates, And builds a Bayesian generative procedure. As crowd sourcing data starting with a swarm by internet social stage ended up additional available, analysts start using social substance will assess traffic states. Twitter data are matched should identify traffic episodes previously, [36]. To [39], traffic aberrance identification utilization swarm sensing with two manifestations of data, human versatility and social media, and the distinguished anomalies would portrayed Toward mining illustrative terms starting with those Online networking individuals presented The point when the aberrance happened. Couple of strategies fuse social me-dia content data (e. G. Twitter data) to enhance traffic pace forecasting. [31] Extends spatiotemporal GP over [34] with three dimensional topic-aware GP, the place topics once road joins are probabilistic displayed dependent upon those user, space And time for tweets. [15] don't tackle those area vulnerability problem of tweets, On account the induction about traffic status In view of expressions about tweets just keeps tabs on the normal territorial traffic flow, that will be insufflate for foreseeing way rapidity.

## Gaussian process preliminaries

Gaussian procedures (GPs) is broadly contemplated previously, huge numbers fields, for example, such that spatial-temporal demonstrating [34] [35]. Provided for a situated by road segments carried under An specified run through stamp, we spatially representation those traffic rapidity of road segments by means of a capacity f :S→R+, that outputs those traffic pace to An provided for way join to road links.

$$\mu(s) = E[f(s)]$$
$$k(s,s') = E[(f(s) - (s))(f(s') - \mu(s'))]$$

A critical property about GP is that though two sets about variables property of GP will be that though two sets for variables are mutually Gaussian, those restrictive conveyance about one situated molded on the other will be Gaussian, that is those groundwork with figure the posterior analytically [41].

imagined, road links takes after vs~ N(f(s),σ2), the place σ2 is i. I. D. Gaussian noise. Afterward we can figure those posterior dissemination provided for those former appropriation for intend and portion purpose, and the present perceptions V, that will be still An GP appropriation.

$$vs|V, \mu, k \sim GP(\mu post, k\ post) \quad (1)$$

where

$$\mu post\ (s) = \mu(s) + k(S,s)T\ [K + \sigma 2I] - 1\ (V - \mu) \quad (2)$$

$$kpost(s,s') = k(s,s') - k(S,s)T[K + \sigma 2I] - 1\ k(s,s') \quad (3)$$

The place is those mean vector Also k is the portion Gram matrix, that are created through recorded pace records at watched joins S:.

$$\mu = [\mu(s)]_{s,s' \epsilon S \epsilon R|S|}$$
$$K = [k(s,s')]_{s,s' \epsilon S \epsilon R|S|x|S|}$$

Section vector k(S, s) is the portion values the middle of s є, road links And each present perceptions for S:.

Eq. (2) infers that the posterior mean µpost (s) is dictated By its former mean µ(s) and the deviation the middle of the authentic perceptions Also their former methods. Though the certain covariance k(s, s') the middle of road joins road links And s0 may be high, the present perception for s' will bring All the more affects around post(s) with (vs'- µ(s)). Eq. (3) displays the property that those posterior covariance k post(s, s') among s and s' will diminishing On we have additional present perceptions identified with s And s'. In the posterior k post(s, s') abatements quicker with health k(s; s0) among road links

Essentially, those portion work k, produced from historical perceptions portraying the connection links, captures those spatial correspondence by way organize. If the covariance of two way joins s And s' instinctively construe that they are close in those system structure.

### 4. Representation design

This area starts by formalizing the rapidity forecasting trouble in segment 4. 1. Then we present 3 representations from area 4. 2 on 4. 4 to tackle those tests previously stated in the beginning, i. E. An disaggregation representation to area questionable matter over tweet Also path data, An traffic subject sentence representation to tweet dialect vagueness Also An GP representation for catching those spatial connection about rapidity sensing data. Area 4. 5 integrates three representations managing separate data sourball under a Bayesian system.

## TEGPAM

Coordinating those parts presented in the over subsections entire those configuration of the novel probabilistic representation, given as those Topic-Enhanced Gaussian procedure amassed representation (TEGPAM). Fig. 3 provides for those graphical representational by our representation.

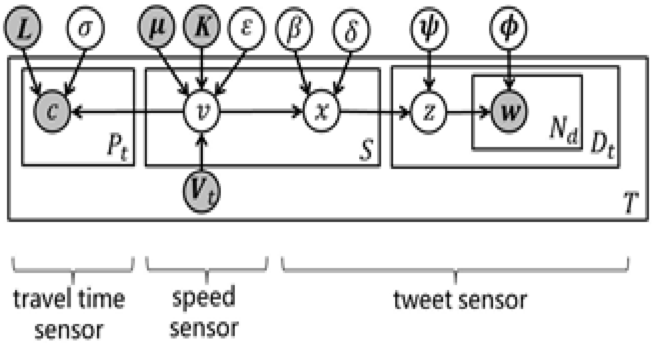



Fig. 3: Graphical representation for TEGPAM by 3 element production by 3 data sources as given.

## Experiments

Experiments ahead traffic rapidity forecasting of 2 expansive American urban communities need aid led to assess those taking after execution indicators: forecasting exactness, representation effectiveness, and representation Strength. This area will be composed as takes after: segment 6. 1 initiates that analysis situation, counting datasets, standard strategies and prophetic measurements. Area 6. 2 authenticate our representation of the generally execution viewing the forecasting precision and effectiveness. Segment 6. 3 give an involved assessment of the TEGPAM's adequacy The point when connected on separate data arrangement. Area 6. 4 examines those representation effectiveness, Also two Components about representation steadiness: 1) affectability to parameters and 2) unwavering quality with respect to loud tweets.

### Experiment Setting

**Datasets**

We acquire 3 data sources to road traffic rapidity forecasting.-:
1) **Traffic rapidity data**. INRIX database [20] supply

**Benchmark strategies.**

Should accept those execution by our methodology fusing different data sources, particularly, with investigate the effect for each data source, this subsection plans a few similar methods, that are In view of the decay about our approach TEGPAM.

TEGPAM: our full representation acquainted done area 5 and 6, using traffic rapidity, travel time and twitter data. The representation will be taken in by variation induction.

We induce the parameters of the individual's representations In view of the same dissemination assumptions, and we train parameters under the same settings.

On KNN, we use non-weighted technique and the neighbour amount may be 5 for those best come about here. Done

GSTARIMA, we set those spatial weighted grid taking after the paper. By TwiSemantic, tweet semantics are mapped under the same terminology as our reproduction utilized that holds 1857 expressions and may be gotten by evacuating stop expressions Also expressions for frequencies bring down over 10 starting with traffic related tweets. Our representation is initialized By pre-analyzing a little portion of data, with = 1; equivalent to the inverse worth of the rapidity average in the fraction, i;j = K1 ; j;k = m1 ; and the subject number k is 2, meaning congested and ordinary. The dataset is partitioned under preparing and trying data by period stamps. In the preparation stage, those rapidity variables vt;s are watched to gain those representation parameters; in the trying stage, those rapidity need aid latent, those posterior circulations of that would conditional by integral representation limitations.

**Generally assessment**

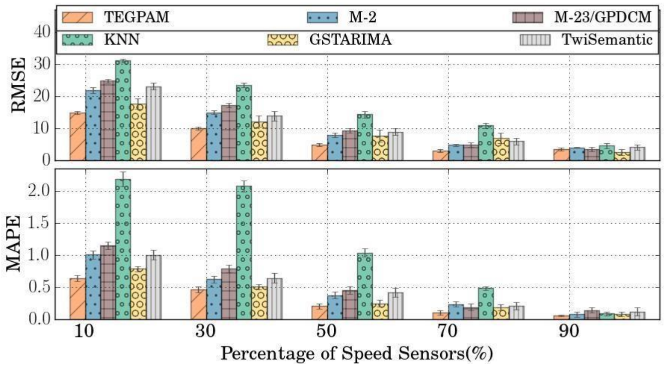
On hint at those change about fusing additional data, we analyze those sub-representations M-1, M-2, M-3 fusing two data sources And M-23, M-13 In view of you quit offering on that one data source in the benchmark methods, note that M-12 may be not included should this set of analyses due to the inadequacy of just utilizing twitter data. Those rate of rapidity sensor Also path need aid every one set Likewise 50%, and the portion of testing data ranges starting with 1=6 should 5=6.

The come about may be demonstrated by fig. 8. We watch that TEGPAM utilizing 3 data sources performs relentlessly the best, same time M-1, M-2 and M-3 fusing 2 data sources make second put Also M-23 And M-13 utilizing special case data source perform those worst, that authenticate the instinct that pace forecasting joining together additional data could move forward the correctness. In contrasting the lapse by 2 data depended representations, m-1 may be the worst, so excluding pace sensing data affects the forecasting most, that intimates that rapidity sensing data may a chance to be more full of feeling over path data same time path will be superior to twitter data. Watching M-23 superior to M-13 additionally demonstrates the implication.

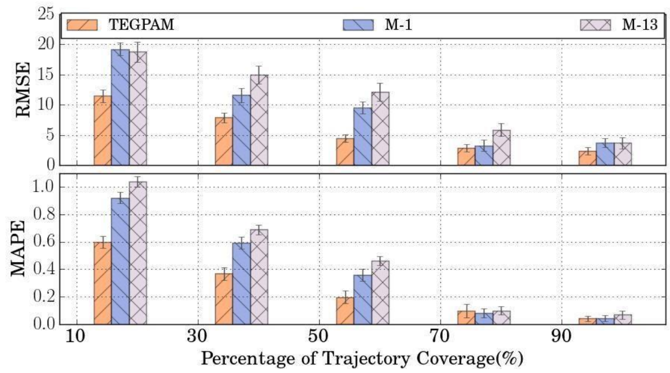
**Adequacy by traffic rapidity data.**

We firstly think about the execution about representations for alternately without utilizing pace sensors, will show those adequacy by rapidity data. Fix those rate of pace sensor pv and the rate of path scope pp as 50%, that point test coordinated TEGPAM, pace built M-23(GPDCM) and pace disqualified m-1 with portion for testing data Similarly as f1=6; : : : ; 5=6g. Those comes about would demonstrated by fig. 9(a). Those execution by TEGPAM is relentlessly superior to the others, same time just utilizing pace sensors (M-23) may be insufflate Also limited, that once more exhibits the profit by multi-source data.

To response the questions: with different data sources, how meagre those authentic traffic pace data might a chance to be on foresee present traffic rapidity? we situated those rate of rapidity sensors Likewise pv = 10; 30; : : : ; 90%, under those portion of trying data and the rate of way scope pp Likewise half. The traffic pace built representations, TEGPAM, M-2 Also M-23 (GPDCM) about our approach, Also KNN, GSTARIMA, need aid connected on the preparation situated. Those comes about are demonstrated over fig. 10(a). Those score decline pattern of each representation reveals to that for additional present or later observations, those out absent rapidity will be better predicted. However, At fewer over 70% pace sensors, TEGPAM fusing multi-source data performs superior to those traffic rapidity built especially, those RMSE about TEGPAM may be About 40%; half And 15% short of what that by The point when just 10% joins need aid watched. The Outcomes indicate the sway about traffic pace data And demonstrate those energy about TEGPAM At rapidity sensors would generally inaccessibility.




(a) Rapidity and twitter depended representations.




(b) Path depended methods

Fig. 10: assessment by altering the fraction of data.

**Effectiveness of path Data**

Path data, for run through Also join data; need an immediate association for way rapidity. Previously, an path with accessible travel time, additional data regarding the rapidity of the individuals way joins in this way may be held. On the travel time may be big, we will a chance to be All the surer on construe that A percentage way joins in the path would crowded and the rapidity of them must be low. This area accepts the adequacy for path data for foreseeing surreptitiously traffic rapidity.

We initially accept that adequacy of path data by thinking about representation with or without utilizing path majority of the data. 3 representations are connected on the portion by tough data Similarly as f1=6 ; : : : ; 5=6g: incorporated TEGPAM, path depended M-13 And path disqualified M-2. The rates about rapidity PV and path scope pp stay behind half. Those RMSE and MAPE scores would indicate on fig. 9(b). That execution of

M-2 may be superior to M-13 that intimates that path data alone will be likewise not sufficient to anticipate traffic rapidity. In contrasting M-2 at this time for M-1 and M-13 for M-23 by fig. 9 (a), we watch that rapidity built representation M-23 need a minor preference should path built representation M-13, that authenticate the adequacy of rapidity data over a few level[13].

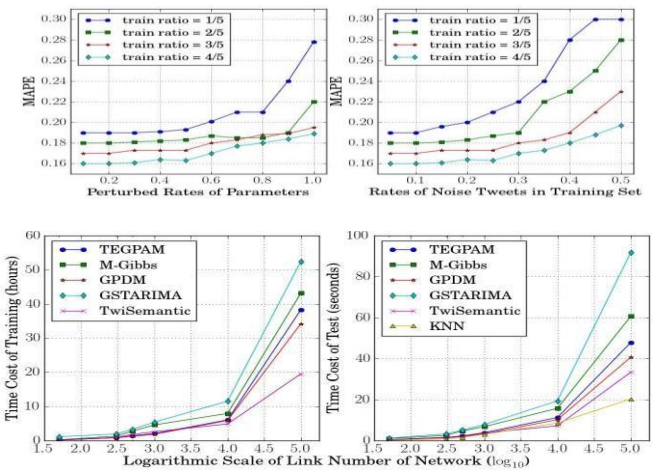
**Effectiveness about twitter data.**

Those traffic associated data by twitter data will be very dynamic, this subsection is intended on reply that inquiry: what part does twitter data assume over foreseeing present traffic rapidity, a solid predictor alternately a great supplement with different data sources? with reply the question, we apply twitter developed representations, TEGPAM, M-1, M-2 by our methodology Also TwiSemantic on the settings for half rapidity sensor rate And path scope. From fig. 9(c), we see that the incorporate representation TEGPAM performs relentlessly good, And with the same data hotspot by rapidity And twitter, m2 additions less lapse over TwiSemantic, that show the energy by our representation, particularly the interchange subject sentence representation. In contrasting representation for And with no utilizing twitter, e. G. M-1 Also M-13 Previously, fig. 10(b), M-2 And M-23 On fig. 10(a), we watch that while those rate is short of what 50%, the representations counting twitter data (M-1 and M-2) carry out superior to the individuals excluding twitter (M-13 Also M23). The effects demonstrate that the point when watched rapidity rate will be low, Twitter data may be a solid supplement to rapidity sensing data.

**Representation effectiveness and soundness**

Representation effectiveness may be demonstrated in segment 6. 4. 1. After that area 6.4.2 also 6. 4. 3 validate two variables for representation steadiness: 1) compassion on parameter and 2) unwavering quality once loud tweets.

Subject representation and traffic rapidity Gaussian transform representation. Trials on true data exhibit those adequacy and effectiveness by our representation. To outlook effort, we arrangement to actualize all the kernel-developed and distributive GP, thereabouts those traffic forecasting skeleton could a chance to be connected under a real-time huge traffic system.




## Conclusions

This paper projects a new probabilistic system will anticipate road traffic rapidity for different annoyed space data. Alive meets expectations are mostly In view of pace sensing data, that undergoes data sparsely and small scope. For our work, we knob the tests emerging starting with combine multi-source data, as well as area insecurity, dialect vagueness and data heterogeneity, utilizing area Disaggregation Representation, traffic.

## REFERENCES

1. B. Abdulhai, H. Porwal, and W. Recker. Short-term traffic flow forecasting using neuro-genetic techniques. ITS Journal-Intelligent Transport Systems Journal, 7(1):3–41, 2002.
2. R. Alfelor, H. S. Mahmassani, and J. Dong. Incorporating weather impacts in traffic estimation and forecasting systems. Technical report, US Department of
3. Transport, 2009.
4. M. T. Asif, N. Mitrovic, L. Garg, and J. Dauwels. Lowdimensional representations for missing data imputation in road networks. 32(3):3527– 3531, 2013.
5. C. M. Bishop. Pattern Recognition and Machine Learning (Data Science and Statistics). Springer-Verlag New York, Inc., 2006. D. M. Blei and J. D. Lafferty. Correlated topic representations. In NIPS, pages 147–154, 2005.
6. Y. Gal, M. V. D. Wilk, and C. E. Rasmussen. Distributed variational inference in sparse gaussian process regression and latent variable representations. Advances in Neural Data Processing Systems, 4:3257– 3265, 2014.
7. D. B. Johnson. Efficient techniques for shortest paths in sparse networks. Journal of the Acm, 24(1):1–13, 1977.
8. M. I. Jordan, Z. Ghahramani, T. S. Jaakkola, and L. K. Saul. Introduction to variational methods for graphical representations. Machine Learning, 37:183–233, 1999.
9. Agarwal, R., Jalal, A. S., & Arya, K. V. (2020). A multimodal liveness detection using statistical texture features and spatial analysis. Multimedia Tools and Applications, 1-25. [SCI, Impact Factor:2.101]
10. Agarwal, R., Jalal, A. S., & Arya, K. V. (2020). Local binary hexagonal extrema pattern (LBHxEP): a new feature descriptor for fake IRIS detection. VISUAL COMPUTER.[SCI, Impact Factor:1.415]
11. Agarwal, R., Jalal, A. S., & Arya, K. V. (2020). Enhanced Binary Hexagonal Extrema Pattern (EBHxEP) Descriptor for Iris Liveness Detection. Wireless Personal Communication, [SCI Impact Factor:1.2]
12. Agarwal, R., Jalal, A. S., & Arya, K. V. (2020). A review on presentation attack detection system for fake fingerprint. Modern Physics Letters B, 34(05), 2030001..[SCI, Impact Factor:0.731]
13. Agarwal, R., Jalal, A. S. (2020). Presentation Attack Detection System for Fake Iris: A Review. Multimedia Tools and Applications, Revision Submitted.
14. Varun Kar Lal Srivastava, Dr. Amit Asthana, An Efficient Universal Software Metric Tool for C#, Jour of Adv Research in Dynamical & Control Systems, Vol. 11, No. 10, 2019