International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

An Efficient Multilevel Framework for Prediction of Optimized Ambulance Routes Using Random Forest Classifier

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Submitted: 14/08/2022 **Accepted:** 21/11/2022

***Abstract*:** Ambulance Routing has been a classical research problem for years because of its multiple constraints and multiple objectives. While the primary objective is to save human Life, finding optimistic routes for Ambulances to transfer the patient to the nearest hospital by travelling in traffic congested routes during peak and non-peak hours with quick response time and minimized total cycle time remains a major challenge.While several techniques, Mathematical models and algorithms are used to arrive at a solution, data mining and machine learning techniques provides efficient methods in achieving the optimal results for the Ambulance Routing Problem. In this paper, Multilevel framework is developed for predicting the Optimized Ambulance routes using Random Forest Classification Trees. First, by using Advanced A* Algorithm the routes are determined for the Ambulances during peak and non-peak hours of traffic. The routes are calculated using the minimum dispersion index as a heuristics along with other constraints such as speed of the Vehicle, distance, number of vehicles crossing each junctions to assess the traffic conditions. Random Forest Classifier is used on the spatiotemporal data sets such as time of starting of Ambulance and the alternate route taken to predict the optimized routes which helps in further improving the response time and total cycle time. The criticial spatiotemporal features required to predict the Optimized Ambulance Routes are very well brought out by using Random Forest Trees.The experimental results reveals that the predicted routes improves the response time by 30 % and total cycle time by 40 %.

Keywords*: Random Forest Classifier, RFsp(Random Forest for Spatial Prediction), Response time ,Spatio temporal data,Total Cycle time.*

1. Introduction

Ambulance routing problem comprises of various complexities, constraints and objectives. It requires careful planning of the route to be taken by ambulances during peak and non-peak time. It has been a research problem for years now as it is the most essential services which requires high degree of success in execution to save human life. The various constraints and objectives are the identification of road network and accident location, real time tracking of ambulance positions, to find quickest routes to reach to the accident spot to pick up the patient and then transfer to hospital, routes to be taken by ambulance during peak hours of traffic, to minimize response time and total cycle time. All these constraints are rich spatio temporal data sets which play key role in determining the optimal ambulance routes.

Many researchers have devised various algorithms, techniques and strategies to arrive at the optimistic solution to the problem. Various algorithms such as Mathematical formulation, Ant Colony Optimization(ACO) algorithm, Particle Swarm Optimization (PSO) algorithm, Clustering algorithms, Genetic algorithm, Nearest Neighbourhood search algorithm are used to solve this problem, but doesn't provide optimal solution as these methods have limitations such as solution is for static scenario, difficulty in structuring the problem, doesn't converge to solution, increased processing time etc..,

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Several techniques using IOT devices, Controlling of traffic signals, micro controller are used but doesn't provide optimal solutions as it is not cost effective, maintenance, controlling and monitoring is difficult. Many heuristics based algorithms such as A*, AO*, Dijksthra's are used. Proper selection of heuristics is essential to achieve optimal solution to ARP(Ambulance Routing Problem).

As mentioned above the spatio temporal datasets involved holds several key information which can help in efficient design and development of solution to the ARP problem. A thorough analysis of these datasets is essential. Today various technologies have evolved such as data mining and machine learning techniques which can analyse these spatio temporal datasets.The prominent one used for spatial and temporal data classification are the decision trees and Random Forest Classification method. The random forest classification method is described as the best supervised machine learning technique to be used with spatio temporal data for prediction. The Multilevel framework is proposed for predicting the optimized Ambulance routes using Random forest Classifier.

Further the paper is organized as follows : Section 2 comprises of important literature review on usage of Random forest for prediction and its usage with spatio temporal datasets and variables, dynamic route selection algorithm. Section 3 explains the Methodology used in the multilevel framework for optimized Ambulance route prediction. Section 4 explains the Area of study and the implementation of experiment. Section 5 explains the experimental results and performance evaluation. Section 6 conclusion with achievements of the experiments conducted, Scope and Limitations.

2. Related Work

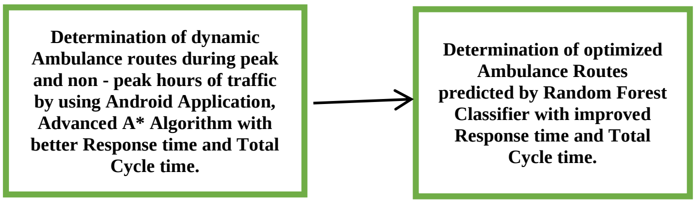
The selection of routes for Ambulance during peak and non peak hours dynamically plays a key role in Ambulance routing as time saving is a primary concern in Ambulance routing. A proper dynamic algorithm which can give the fastest route (need not be the shortest route) during peak and non peak traffic is essential. Noraimi et al [1] explains the usage of A* Algorithm in finding the shortest path for Ambulances in Malaysia with 10 minutes response time. He also mentions that the heuristics based algorithm works better and gives efficient results for Ambulance Routing problem. S. Panahi and M.R. Delavar [16] have devised a Decision Support system with GIS to find dynamic shortest paths for Ambulances in Tehran, Iran. They explain that it is difficult to construct and find all the routes including the alternative routes for the city using GIS. It is difficult to get the efficency. Elgarej Mouhcine et al [17] have used the distributed Ant colony optimization method for calculating all the routes in the city of Morocco. This is time consuming process and is not well suited of Ambulance routing problem which has a time constraint.Yan Huang et al [18] have devised a framework for identifying the spatiotemporal sequential patterns which are crucial for deriving event patterns in many applications. They define each event with event ID, time, location, and event type forming data sets. This type of a framework and data set are crucial for event analysis and Mining patterns. Xiaolei et al [19] have devised a method for outlier detection in traffic temporal data by using the probability distribution and including the local outlier factor by extending the database where outliers are considered as in liners. These methods help to sort out the spatio temporal datasets and makes it ready for analysis. Wei Liu et al [20] have devised algorithm by building trees to find out the spatio-temporal causal interactions in streams of traffic data. The traffic data streams comprise of several unusual types of spatio temporal data sets which represents several abnormal datasets due to celebrations, traffic jams due to road blocks etc. such types of causal interactions in traffic data streams need to be handled so that the actual traffic data become clear. S. Kim et al [21] have devised real-time traffic information for vehicle routing problem in nonstationary stochastic network with Markov decision process formulation. S.Nagamani et al [2] have proposed heuristic based solution by devising a new algorithm known as Advanced A* Algorithm using Dispersion factor which calculates the fastest path by using alternative routes with quick response time and total cycle time. With the selection of fastest heuristics with various constraints and objectives, we can achieve minimized total distance as explained by Y. Caseau et.al [15].

Tomislav Hengl et al [3] have explained random forest for spatial predictions framework (RFsp) in which geographical observation points can be included in prediction process and how it can be applied to Categorical, numerical, binary, multivariate and spatio temporal variables which gives accurate results.Timothy Supinie et al [4] have explained and used spatio temporal Relational Random Forests to predict and study the turbulence and connectivity of Commercial Airlines in United States. Hassan Talebi et al [5] have used random forest classification in Geoscience to study the vectorised spatial patterns and co- variants relationships of variables in Queensland, Australia. The spatial data are used as inputs for geological mapping, in prediction of geochemical patterns, and in analysis of discovered process. Chan, T. Boutilier et al [6] describe a method for optimizing the location and routes for Ambulances with uncertain travel time and spatial demands of economically poor Countries. The experiment was conducted in Dhaka and Bangladesh. The datasets comprised of simulated data, estimated datasets and with machine learning techniques such as Random Forest and linear regression with k-nearest neighhour algorithm with travel time prediction. They mention that the random forests gives best results. Navarro- Espinoza et al [7] have devised an adaptive traffic controlling system with traffic light control or by adjusting the timing of traffic lights for predicted traffic at an intersection by using machine learning algorithm. Gaurav Meena et al [8] have used Decision trees for traffic prediction for Intelligent Transport System. Kanevski M et al [9] have analysed applications which manages spatial data with uncertainity and randomness in few complex structures. Ham J.Chen et al [10] discuss about the critical problem of handling of the high dimensional spatial data in achieving optimization.Gangappa et al [11] discuss various supervised learning algorithms used in geospatial objects prediction such as Support Vector Machine algorithm ,decision trees and Random forest trees. Hexiang Bai et al [12] discuss about vagueness of data objects using set theory with smaller and higher approximations. The smaller approximation defines objects with relativity to the concept and higher approximation includes with possible objects relative to the concept. The boundary region gives the vagueness between smaller and higher approximations.Abhniaya Mohan et al [13] discuss about the application of the SMOreg method which shows better results for Spatio-temporal data sets. Yuan H et al [14] mentions that traffic predictions at different times of the day is a critical component in building Intelligent Transport system for Smart cities.

It is clear that Random Forest Classifier works better for the Spatio Temporal variables and datasets and gives better accuracy in predicting the intended results. Hence, the Random Forest Classification method can play a key role in analyzing Ambulance routing spatio temporal datasets such as location of accident/patient, ambulance movement and the time acquired for ambulance tracking, patient pickup time and time of admitting patient to hospital, routes taken etc.., and for predicting the optimized ambulance routes efficiently.

3. Methodology

The Multilevel strategy Approach is used to get the optimal solution for Ambulance Routing problem as it comprises of multiple objectives and constraints. This section explains the Multilevel Framework proposed with two phases for the determination of optimized Ambulance routes by using Random forest Classifier.



PHASE 1 **PHASE 2**

Figure 1: Proposed Multilevel Framework with 2 phases to achieve Optimized Ambulance Routes using Random Forest Classifier

The following procedure is followed to derive the optimized Ambulance routes using the above multilevel Framework with Advanced A* Algorithm and Random Forest classifier.

PHASE 1) The Multilevel framework with Android application and Advanced A* Algorithm is used to derive the fastest route taken by ambulance during peak and non-peak hours of traffic by achieving the optimal response time and total cycle time.
This framework reduces time in 3 stages and saves more than 20 to 35 minutes against the standard procedure that is currently followed.

PHASE 2) Further improvement in response time and total cycle time is achieved by using route taken spatio temporal datasets with random forest classifier which predicts the optimized Ambulance routes to be taken during peak and non-peak time. These predicted routes are based on the start time of Ambulance (peak or non-peak traffic time) and the location
.

Both the phases are explained in detail below.
It is observed that the following optimal features plays a key role towards achieving solution to Ambulance routing. Hence the following features are considered.
i) Peak Time Traffic with Medium and High Traffic congestion hours and Non-Peak with Low hours of Traffic Congestion
ii) Number of Vehicles Crossing junctions in an hour & at any given instance of time.
iii) Speed of Vehicles during Low, Medium and High Traffic Congestions .
iv) Delay at Junctions during Low, Medium and High Traffic Congestions.
v) Spatio Temporal Datasets (Spatial- Ambulance and patient Location and
Temporal- Time where Ambulance is in Movement at any given instance of time).

vi) **Response Time** : Duration of time from the time the ambulance is booked and until it reaches the accident spot to pick up the injured patient.

vii) **Total Cycle Time** : Duration of time since the time the ambulance was called, picked up the injured patient and untill the patient is admitted in hospital.

The optimized routes generated should minimize the response time and total cycle time i.e.,, should have quick response time and total cycle time.

In the first Phase, the following multilevel framework as depicted in Figure 2 and 3 (S.Nagamani et al [2]) comprising of Android application with user App and Driver App with the routes determination by Advanced A* Algorithm is used to determine dynamic routes taken by ambulance during peak and non-peak hours.
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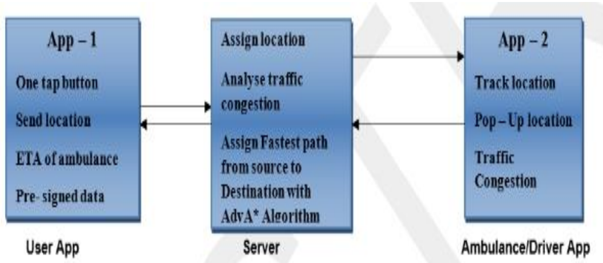

Figure 2: THE MULTILEVEL FRAMEWORK

Figure 3 : Alert using RFID Reflectors

The following strategy aims at achieving quick response time and total cycle time by
saving time at various stages :
I) Android Application comprises of User App to book the ambulance and the Driver App will immediately show the location of the Victim and the driver rushes to the pick up the victim. Ambulance is automatically assigned. The information about the patient can be recorded in a form. This helps in achieving quick response time by saving 5 to 7 minutes. The ETA (Estimated Time of Arrival) of the Ambulance and driver contact number is displayed in user application.

II) The Advanced A* Algorithm with Dispersion factor computes the fastest optimal routes with dynamic traffic conditions using the non-congested alternative routes. This avoids Ambulance getting into heavy traffic congested routes which reduces waiting time and quick mobility towards the destination. This saves 10 to 14 minutes by avoiding traffic congested routes.

The Algorithm works as follows:
The forward node and path is calculated using the formula in equation 1.

$$\text{Min } f(n) = g(n) + h(n) + i(n) \longrightarrow \quad (1)$$

g(n) is the distance between the initial node to current node and h(n) is the distance between the current node to destination node as described in A* Algorithm
i(n) is the heuristic Dispersion component introduced as a function with i as the Dispersion index which is calculated using equation 2. i(n) helps in forward node selection iat traffic junctions . The Dispersion index i(n) is defined as a set of values between 0.0 and 1.0.

$$i(n)=\text{Min} \sum_{i=1}^{n} \left[\frac{\text{Length (node)}}{\sum_{i=1}^{n} \text{Length (All Adjacent Nodes)}} \right] \longrightarrow (2)$$

If at any intermediate node from Start to Destination node, the vehicle stops waiting for 40 secs or more and the next node is not a single route than alternative route is selected the remaining route nodes with Minimum Dispersion index computed using equation 2 else if waiting time >=40secs and next node is a single route to destination then continue with same route forward by calculating the minimum Dispersion index using equation 2.

The Algorithm generates the following data comprising of the attributes such as callid, place or starting location, time of starting and reaching different junctions and finally destination hospital, Junctions it is crossing before reaching destination,response time(RT), total cycle time(TCT), distance, speed, delay, ETA(in minutes), ETA.

III) In third strategy using LED lights is used in single routes and traffic signals as depicted in Figure 3 which glows and gives indication toe people that the Ambulance is coming in that route and they should give way for it. This strategy reduces 5 to 6 minutes in overall time.

Estimated Travel Time (ETA) Calculation –

The Estimated Travel time or Estimated time of arrival is calculated using the following equations:
ETA Calculation = start time + (Distance /Speed) * fraction part with 60 ----------> (3)

Considering the Delay during Low, Medium and High Traffic Congestion's the ETA is calculated using the equation

ETA Calculation + Average number of junctions crossing * Delay in secs ----------> (4)

In the Second Phase, the random forest classifier algorithm is used to further improve the response time and total cycle time. Using the spatio temporal datasets generated in phase 1 such as ambulance start time, location, route taken while crossing different junctions during peak and non-peak traffic hours is taken as input to the random forest classifier algorithm. The random forest classifier algorithm predicts the optimized ambulance routes to be taken during peak and non-peak hours of traffic starting from a location.

The Random Forest Algorithm is described as follows:

1) Read the predictors data such as start location, peak or non-peak time, routes taken, delay from the table.
2) Define the target variable - Route1 for route prediction.
3) Train the model using 70:30 ratio training set and test data set.
4) Use Random Forest Classifier with criterion as “gini” and estimators to predict the optimized ambulance routes.
5) Print the model Accuracy for correctness.
6) Plot the Random Forest Tree.

The algorithm is implemented in python.

The random forest as in figure 4 is a decision tree based supervised machine learning method which uses ensemble learning technique with multiple classifiers to solve complex problems.. A meta bootstrap accurate algorithm known as Bagging is used to train the data in random forest The random forest method forecasts by using averaging the output of different trees. The precision of the result gets better by with reduced over fitting of datasets as the tree grows in number.

The observed attributes are grouped together as training datasets used for preditions. The random trees will be ranked, and the one with the good score is selected as the final product.

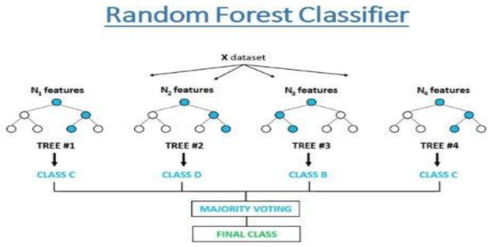

Figure 4: Random Forest Classifier

Tomislav Hengl et al [3] have mentioned that random forest is the best technique that can be included in prediction process and it is applicable to various spatio temporal variables which gives accurate results.

Use Case 1)

The following example explains the working of Advanced A* Algorithm with Dispersion Index.

Consider the Search Graph G in figure 5:
If the next node A is Congested (Marked in red with waiting time >=40 sec) the node A is deleted from the list selected.
Other Alternative nodes i.e.., B and C are taken in to consideration. So, the node with minimum Dispersion index B is selected.

S -->B.

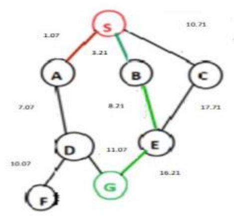

Figure 5 : Search Graph

Using Equation 2, i(n) is calculated.
Here let us calculate i(n) for say from S to A
i(n) = 1/(1+3+10) = 0.07

Using in Equation 1 Min F(n) = 0+1+0.07 = 1.07
Similarly, Dispersion index is calculated for all nodes as in figure 6 and values depicted in Table 1.

So, the Dynamic route selected is
S -->B--> E -->G.

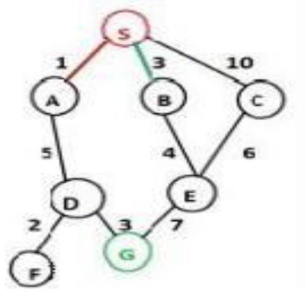

Figure 6: Graph with Dispersion Index

Node	F with Dispersion index	Path to Goal Node G
A	11.07	S→A→D→G
B	16.21	S→B→E→G
C	25.71	Is not considered as C→E is not Min
D	11.07	S→A→D→G
E	16.21	S→B→E→G
F	10.07	No path as the goal node G cannot be reached from F

Table 1: Dispersion index for nodes in the Graph and Path

Use Case 2)
The following scenario in figure 7 and 8 explains the improvement in response time and total cycle time before and after using Random Forest Classifier

The nodes represents different junctions : A - Source(Ambulance start location) ,
F- Destination (Hospital) , and B,C,D,E are intermediate junctions.

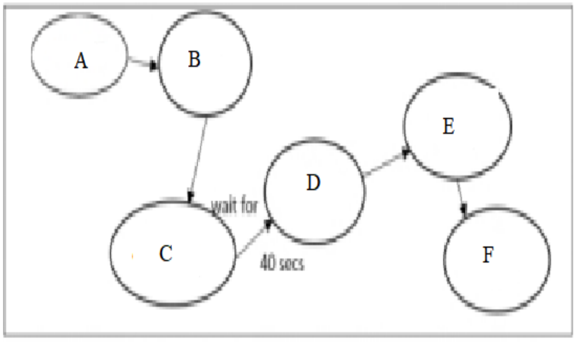

Figure 7: Routes taken to reach hospital before using Random Forest Classifier during Peak - High Traffic

If at any junction (C to D) the ambulance waits for 40 secs in traffic congested route the alternate route is taken to D.

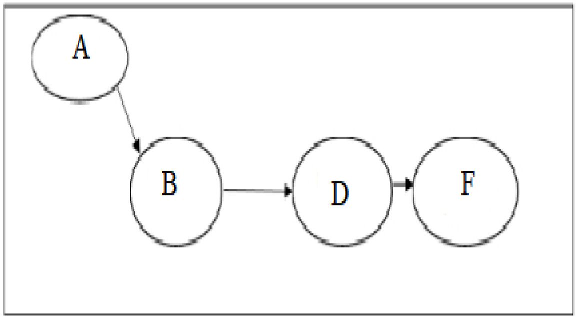

Figure 8 Routes taken to Hospital after using Random Forest Classifier during Peak - High Traffic

The Random forest classifier predicts the route from B to D directly instead of waiting at junction C during peak hours.

4. Area of Study

The GVK EMRI popular 108 Ambulance service in Bangalore is used for case study. With the approval from the Deputy Director, Arogya Kavacha-108, Health and Family Welfare Services Directorate, Government of Karnataka, the three-month call data list is taken for the study and analysed.

The call data list comprises of the following spatio temporal attributes: call identification number,time, accident location, Ambulance number, driver contact number, ambulanced assigned time, arrival time at the accident spot, time of arrival at hospital ,patient admitted time, patient age and gender, case closing time with remarks.

The study reveals that currently when an ambulance is required the victims relative has to call to the 108 BPO call centre and book for ambulance and wait. The Available ambulance has to be checked by BPO staff and has to be assigned and then the ambulance reaches the accident spot pick the victim. The ambulance further takes the shortest path which are mostly congested during peak time and has to reach the hospital. The response time and total cycle time is beyond the golden hour .The Golden Hour Rush of one hour two minutes could not be achieved in more than 71.96% of the cases. There is a need fastest path calculating algorithm and multilevel framework with proper strategy to achieve the intended response time and total cycle time.

The Multilevel framework is implemented in K.R.Puram area in Bangalore which is one among the 13 worst traffic junctions in the city. The Ambulance takes more than 20 to 30 minutes Response Time, Total cycle time is 60 minutes to 135 minutes .

Further details about peak and non-peak time of traffic, traffic delays at junctions, speed of vehicles and number of vehicles crossing junctions have been taken from Bangalore City Traffic Police portal. The details are listed in the table 2 below.

Traffic Congestion Peak /Non-peak Time	Timings	Number of Vehicles Crossing junctions in an hour	Number of Vehicles Crossing junctions at any given instance of Time	Delay at Junctions	Speed of Vehicles
Non-peak Time – Low	6am to 8am, 11am to 1pm, 9pm to 6am	> 50 & <=100	8 – 16 vehicles	10 Sec	16 Km /hr
Peak Time – Medium	1pm to 4pm	>101 & <=220	18-36 vehicles	20 Sec	14 Km/hr
Peak Time - High	8am to 11am, 4pm to 9pm	>220 & <=350	38-58 Vehicles	30sec	11 Km/hr

Table 2 : Peak and Non-peak Timings, Traffic and Delay in area of study

5. Experimental Results and Performance Evaluation

The experiment is conducted in 23 different locations in K.R.Puram during peak and non-peak hours of traffic.

The android application screen shots in Figure 9 & 10 depicts the User Application and Driver Application working.

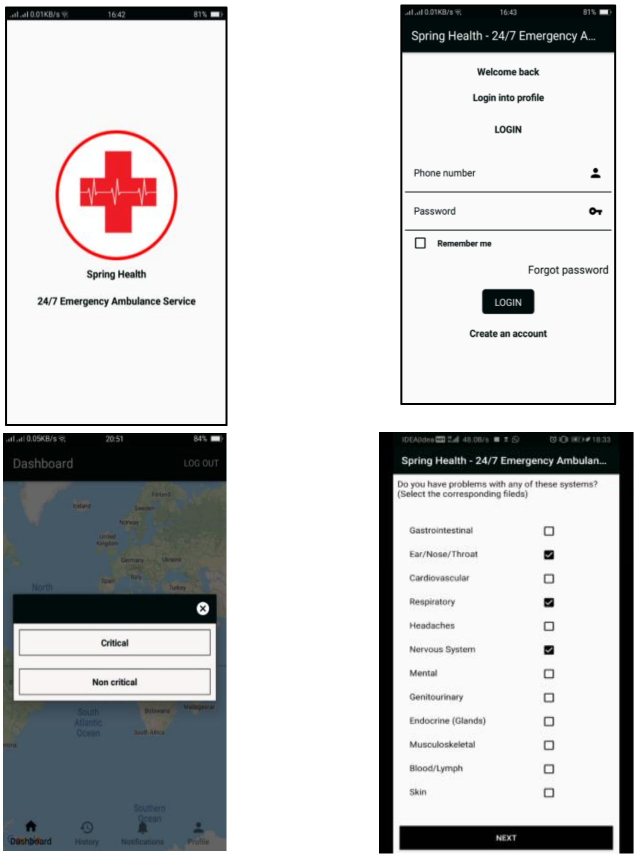

Figure 9: Android Application - User App with login form, ambulance booking for critical and non-criticial cases and patient information form

Figure 10: Android App - Driver App screen shots showing the accident spot with location and time of booking

The Android Application saves 5 to 7 minutes by automatic Ambulance assignment & tracking. Table 3 shows the dynamic Ambulance routes by using Advanced A* Algorithm .

Call Id	Place	Time1	Peak/Nonpeak	Low/ Medium/ High	Junction1	Time 2	Junction2	Time3	Junction3	Time4	Destination	Time5	Response Time (RT)	Total Cycle Time (TCT)	Distance	Speed	Delay	ETA(min)	ETA
1	Galaxy Home, Near Garden City	04:40:18	Nonpeak	Low	TC Palya sign	04:55:38	Govt Scie	05:05:12	KR Puram	05:14:12	TLH, KR PUR	05:21:38	15	41	9.5	16	0.4	00:36:00	5:16:18
2	Near Bhattarahalli	07:29:41	Nonpeak	Low	medhalli Ro	07:42:46	KR Puram	07:52:34	KR Puram	08:00:10	TLH, KR PUR	08:05:46	13	36	5.5	16	0.4	00:22:00	7:51:41
3	Kristu Jyoti College	18:45:00	Peak	High	Narayanapu	19:01:16	SBI Bank	19:16:12	Govt Scie	19:25:08	TLH, KR PUR	19:38:16	16	53	8.8	11	2	00:50:00	19:35:00
4	Indus Valley School	14:02:30	Peak	Medium	church side	14:20:55	Govt Scie	14:42:24	KR Puram	14:53:24	TLH, KR PUR	14:58:55	18	56	9.8	14	1.2	00:43:00	14:45:30
5	Devasandra road	13:11:19	Peak	Medium	Basavanapu	13:32:44	KR Puram	13:49:19	KR Puram	13:52:10	TLH, KR PUR	14:02:44	21	51	8.8	14	1.2	00:38:00	13:49:19
6	SEA College	21:52:57	Nonpeak	Low	KR Puram Sig	22:06:23	KR Puram	22:08:10	KR Puram	22:12:15	TLH, KR PUR	22:22:23	14	29	6.5	16	0.4	00:25:00	22:17:57
7	ITI Extension	07:45:48	Nonpeak	Low	KR Puram Pol	07:55:11	KR Puram	08:05:10	KR Puram	08:10:20	TLH, KR PUR	08:14:10	10	29	6.5	16	0.4	00:25:00	8:10:48
8	Govt First GradeCollege	20:59:54	Peak	High	KR Puram Traffic Police	21:17:04	Church R	21:26:22	KR Puram	21:42:28	TLH, KR PUR	21:53:09	18	54	8.9	11	2	00:50:00	21:49:54

Table 3: Dynamic routes taken by Ambulance by using Advanced A* Algorithm

The Advanced A* Algorithm shows response time of 20 minutes and total cycle time of one hours two minutes (standard Golden Hour Rush time) as established by S.Nagamani et al [2] which is the fastest compared to other popular algorithms such as A*, AO*, Dijksthra's, and swarm based PSO algorithm which consumes lot of time. The Advanced A* Algorithm shows optimal results compared to other popular algorithms in terms of response time, total travel time and total cycle time.

In the second phase of time improvement the route taken as depicted in table 3 is used as input data set for random forest classification algorithm implemented in python code. The code generates the random forest tree with predicted optimized ambulance routes. The optimized Ambulance routes predicted starting at one of the location (at Galaxy Home) is displayed in Figure 12 below.

```
In [6]: runfile('C:/Users/Nagamani Shankar/RFTree.ipy', wdir='C:/Users/Nagamani Shankar')
Accuracy: 100.0 %
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
```

Figure 11: Accuracy of the Random Forest Classifier model implemented in python

The accuracy of the random forest algorithm is 100% as depicted in figure 11.

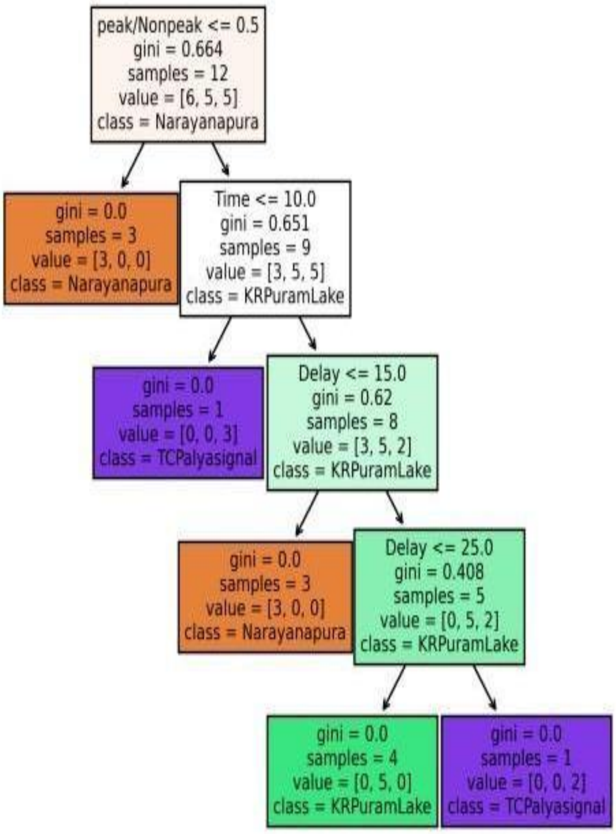

Figure 12: Random Forest Classification Tree for a given Location (Galaxy Home) got by execution of python code

The following table 4 consists of the predicted optimized Ambulance routes for different locations at different starting time (Peak - Medium and High Traffic) and Non-peak (Low Traffic) . It is evident that the routes predicted shows improvement in response time total cycle time.

Sl No	Source	Location	peak/Non	Low/Med	Destinatic	RT (Before)	RT(After)	CT(Before	TCT(After)	Route Predicted	RT- Time saved	TCT-Time Saved
1	Galaxy Home	GA	Nonpeak	Low	TLH Hospi	15	12	41	39	<GalaxyHome,TC	3	2
			Peak	Medium	TLH Hospi	15	10	47	41	<GalaxyHome,KR	5	6
			Peak	High	TLH Hospi	25	22	52	45	<GalaxyHome,Na	3	7
2	6th Main Road , K R Puram	6M	Nonpeak	Low	TLH Hospi	10	9	37	32	<6th Main Road ,	1	5
			Peak	High	TLH Hospi	19	15	59	52	,KR puram	4	7
3	Ayappa Nagar Quarry	AN	Nonpeak	Low	TLH Hospi	7	6	40	37	<Ayappa Nagar Q	1	3
			Peak	Medium	TLH Hospi	24	18	60	49	Quarry,	6	11
			Peak	High	TLH Hospi	20	18	55	50	<Ayappa Nagar Q	2	5

Table 4: Predicted routes with Random Forest Classifier with Response Time (RT) and Total Cycle Time (TCT) Improvement

Figure 13 and 14 below explains the route taken before and after using random forest classifier from one the location Narayanapura to TLH Hospital. It shows how the predicted route saves time.

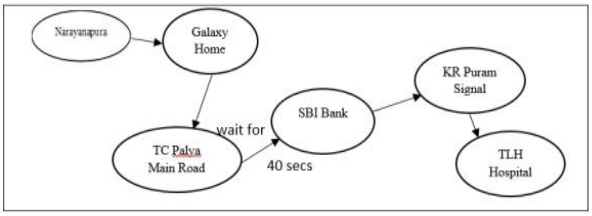

Figure 13 : Routes Determined from Narayanapura to TLH Hospital before using Random Forest Classifier during Peak - High Traffic

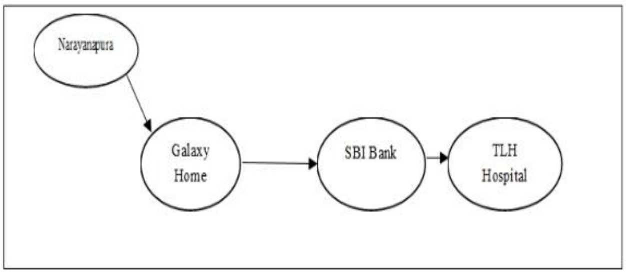

Figure 14 : Routes Determined from Narayanapura to TLH Hospital after using Random Forest Classifier during Peak - High Traffic which saves 6 to 12 minutes TCT

The results shows that in more then 87% of the cases the predicted routes have been able to save total cycle time and have been able to reach hospital with in one hour two minutes. This is a phenomenal achievement compared to earlier percentage where in more than 71.96% of the cases the patient was not transfered to the hospital in Golden Hour Rush. This clearly indicates that usage of Random Forest Classifier for this problem has been efficient and useful in achieving the desired results.

The following Figure from 15 to 20 shows the Graph plots which compares the response time and total cycle time before and after using random forest classifier in Low, Medium and High Traffic respectively. The Graph shows time saving of 5 to 7 minutes in response time and 6 to 12 minutes in Total Cycle time.

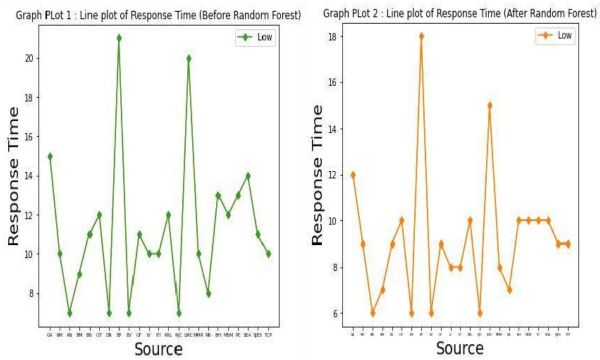

Figure 15: Graph Plots showing comparison of response time before and after using Random Forest Classifier in Low Traffic

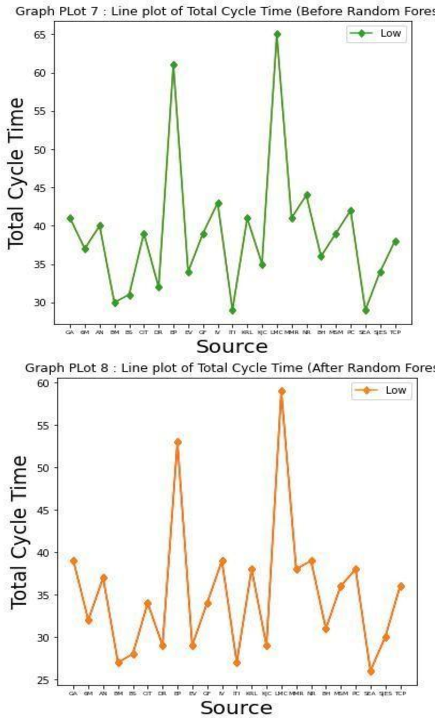

Figure 16: Graph Plots showing comparison of Total Cycle time before and after using Random Forest Classifier in Low Traffic

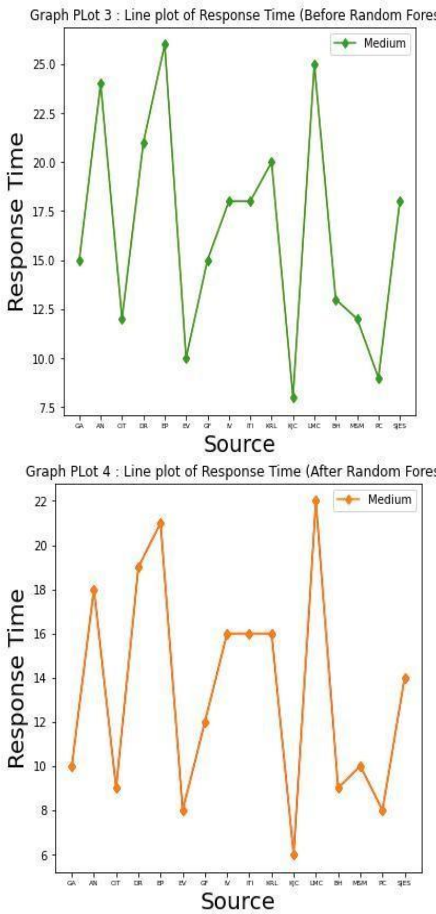

Figure 17: Graph Plots showing comparison of response time before and after using Random Forest Classifier in Medium Traffic

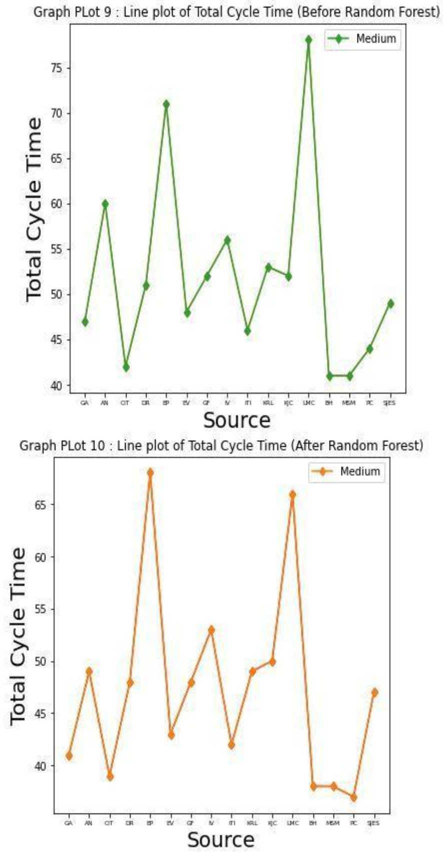

Figure 18: Graph Plots showing comparison of Total Cycle time before and after using Random Forest Classifier in Medium Traffic

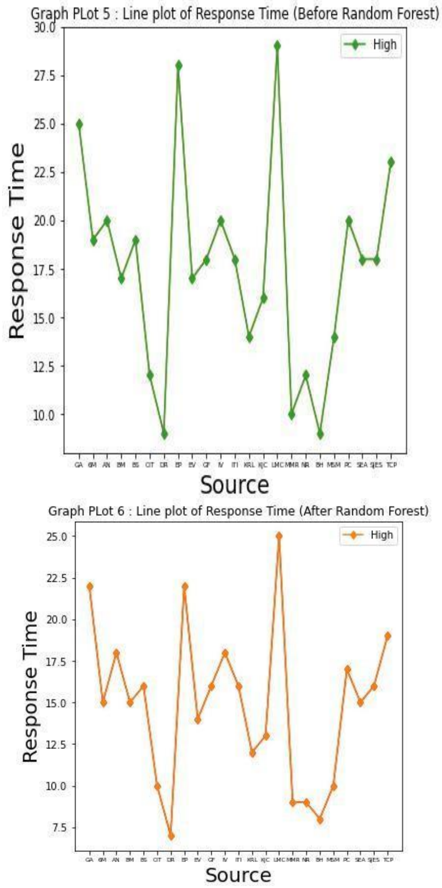

Figure 19: Graph Plots showing comparison of Response time before and after using Random Forest Classifier in High Traffic

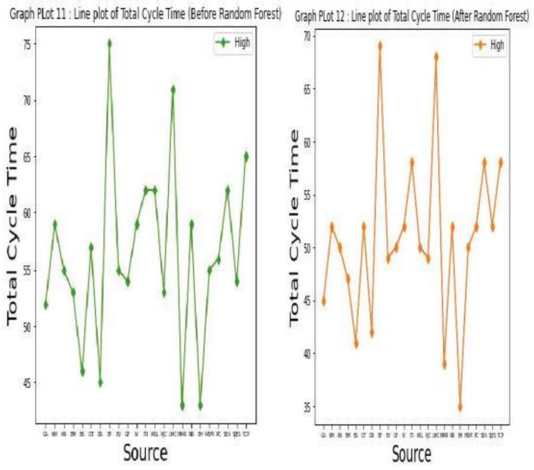

Figure 20: Graph Plots showing comparison of Total Cycle time before and after using Random Forest Classifier in High Traffic

6. Conclusion , Scope & Limitations

Conclusion:

The two phase multi level framework has been able to predict the optimized Ambulance routes during peak and non-peak hours with improved Response time and Total Cycle time by using Random Forest Classifier with 100% Accuracy.

Scope:

- The Multilevel framework can be used globally in any country by carefully considering the various factors which leads to traffic congestion there.
- The Accuracy of the model suggests that Random forest classifier can be used in various real time applications with spatio temporal data to deliver optimal results.
- The model can be implemented to Ambulance routing in India.
- The model can be implemented for other emergency services such as Fire Fighting Engines services, National Disaster management, by police for women security.

Limitations

Better road infrastructure and public awareness towards Ambulances can further improve the response time and total cycle time thereby helps in saving precious human life.

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