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Research Article

Modification of Shortest Path Algorithm for Ambulance in Various Road Conditions for Emergency Patients

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ARTICLE INFO	ABSTRACT

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Road conditions and quality can significantly affect ambulance arrival time. Arrival time can be optimized by choosing the shortest route free from potential congestion. Patient safety during the journey is an essential factor that must be considered. Poor road conditions are one of the factors that can affect patient safety. This study aims to provide ambulance navigation by choosing the shortest safe route for emergency patients in various road conditions. The simulation of finding the shortest route using the modified A* algorithm and the Bellman-Ford algorithm to avoid routes with specific road conditions is an essential factor in the success of this study. The performance of the modified A* and Bellman-Ford algorithms was then evaluated by comparing their accuracy with Google Maps. The modified A* algorithm, namely A* Heuristic Modification and Weight Modification (A*-HMWM) achieved a distance accuracy of 90.92% and a travel time accuracy of 87.66%. The modified Bellman-Ford algorithm, namely Bellman-Ford Weight Modification (BF-WM) achieved a distance accuracy of 92.58% and a travel time accuracy of 91.91%. Both algorithms successfully avoided the edge connecting nodes 61 and 166, which are 300 meters apart, with a road width of 3.5 meters and a road condition quality of 75%. The Bellman-Ford algorithm shows better accuracy than the A* algorithm. The A* algorithm presents a more significant opportunity for development due to its flexible heuristic function. With appropriate modifications to the heuristic function, the accuracy performance of the A* algorithm can be improved for various conditions. Further research is needed to assess the algorithm's performance under real-time conditions with dynamic changes in road density.

Keywords: A* algorithm, Bellman-Ford algorithm, ambulance navigation, road conditions, accuracy, patient safety.

INTRODUCTION

Traffic congestion leads to increased transportation costs and inefficiencies in supply chains [1]. It also impedes the response of emergency vehicles, such as ambulances, which require minimal travel time to save patients' lives in critical situations [2]. Traffic congestion can be categorized into two main types: routine congestion occurring at specific times and locations and sudden, temporary congestion [3]. Accurate traffic prediction is essential for minimizing the impact of congestion and maximizing transportation efficiency [4]. Predictive models can estimate recurring traffic density patterns by analyzing traffic trends from the same day of the previous week [5].

Congestion avoidance algorithms can be implemented in Emergency Vehicles (EVs) as navigation tools to expedite their travel time to their destinations. While traversing transportation networks, these vehicles often face challenges in identifying optimal routes. The optimal route in a transportation network is commonly called the shortest path problem [6]. Depending on the context of the problem, the term "shortest path" may refer to the shortest distance, fastest route, most reliable path, highest-capacity route, and so on. Network routes are characterized by their length, representing distance, travel time, travel cost, route reliability, and other factors [7].

Implementing navigation algorithms is essential to optimizing ambulance travel within complex road networks in densely populated metropolitan areas. Consequently, algorithms such as Dijkstra and A* are frequently utilized to ensure ambulances can reach their destinations in optimal time, particularly in intricate road systems [8]. Dijkstra's algorithm is commonly employed in real-time navigation systems to identify the shortest path due to its high efficiency and execution speed [9]. On the other hand, the A* algorithm, which combines heuristic approaches with shortest path evaluation, demonstrates strong performance in simulation-based GIS systems, achieving efficiency in search time and memory usage [10]. Meanwhile, comparisons between the Bellman-Ford and Dijkstra algorithms indicate that Bellman-Ford excels in handling graphs with negative weights but is slower in terms of time complexity than Dijkstra [11].

Medical professionals often refer to the first hour of emergency care as the "golden hour" for trauma patients [12]. Increased travel distance to the hospital elevates the risk of mortality [13]. Research conducted in Japan indicates that longer travel distances to hospitals are significantly associated with higher mortality rates from cardiac arrest, stroke, and pneumonia [14]. The speed and acceleration of ambulances during transit substantially impact patient conditions and the effectiveness of medical services. Sudden acceleration, whether during speeding up or braking, can hinder medical personnel's performance in providing care, such as reduced quality of chest compressions during CPR due to vehicle instability [15]. Furthermore, unstable acceleration poses a risk of brain injuries, including superficial bleeding, caused by the relative movement of the brain within the skull [16]. Patients with cardiovascular conditions, such as heart attacks, are particularly vulnerable to elevated heart rates induced by vibration intensity during transit, which is often exacerbated by high ambulance speeds [17].

Road unevenness further exacerbates patient conditions and reduces comfort during emergency transportation. Vibrations generated by uneven road surfaces can aggravate patient injuries, including additional trauma and disruptions to internal organs caused by mechanical forces experienced during transit [16]. Patient discomfort significantly increases due to excessive vibrations, which can adversely affect the quality of medical care [18]. Furthermore, the impact of road unevenness on the effectiveness of medical treatment and patient conditions underscores the necessity for ambulance management to prioritize vehicle stability during emergencies [19].

RELATED WORKS

Previous research combined the shortest path algorithm with the Convolutional Neural Network (CNN) VGG19 to provide rapid access to critical locations following natural disasters [20]. The designed model utilized road condition data captured through cameras to identify road objects. These road objects were then classified to determine whether the roads were damaged or not using a convolutional neural network (CNN). Subsequently, the road condition data were employed to assign road weights. This study focused on real-time accuracy in detecting and classifying road damage rather than identifying the shortest route. Another study recommended integrating the Fuzzy-Dijkstra method to identify the shortest path [21]. This approach improved the traditional Dijkstra method, which only considers distance as the weight when determining the shortest path. Adding the Fuzzy Sugeno method allowed road density and segment length to be weighting parameters for each path.

In the context of emergency vehicles, advanced algorithms such as Exponential Bird Swarm Optimization (Exp-BSA) have demonstrated efficient dynamic route planning to avoid congestion, enabling ambulances to reach their destinations in shorter travel times [22]. In emergency vehicle navigation, algorithms such as Particle Swarm Optimization and Ant Colony Optimization can solve shortest path problems by considering distance, travel time, and congestion levels. Data mining-based algorithms have also been proposed to enhance the accuracy and efficiency of traffic flow predictions [23]. Several publicly accessible traffic density datasets are available, such as the traffic density data for Beijing Ring Road [24]. Traffic density data can also be obtained using Maps APIs, such as the Google Maps API. In many parts of the world, Google Maps-based API services provide the most reliable information regarding estimated arrival times and traffic congestion conditions [25].

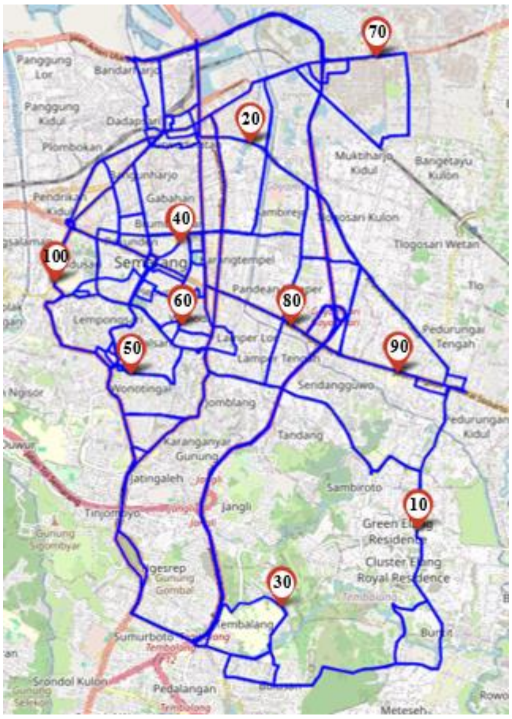
Various shortest path algorithms are commonly used to solve routing problems in navigation systems, including Dijkstra's algorithm, Symmetric Dijkstra, A* algorithm, Bellman-Ford algorithm, Floyd-Warshall algorithm, and Genetic Algorithm. Among these, the A* and Bellman-Ford algorithms demonstrate superior performance compared to the others [26]. The novelty of this study lies in the influence of road conditions on route selection for emergency vehicles (EVs). In this context, road conditions refer to road segment length, width, and, most importantly, road quality (level of road damage). Road quality significantly affects patient conditions during transit. Data on road conditions between hospitals were obtained from the official website of the Semarang City Government [27].

This study will modify the A* and Bellman-Ford algorithms to identify the shortest route for navigating ambulance transfers between hospitals in Semarang, Indonesia, under highly complex road conditions. Inter-hospital ambulance transfers involve moving patients from one hospital to another as referral cases. Traffic data between hospitals were collected using the Google Maps API, which provides estimated travel times for each road segment and road segment length data. The A* and Bellman-Ford algorithms were chosen due to their robust performance in finding the shortest routes [10], [11], [26].

METHODS

Data Resources

This study utilizes data from Semarang City, Indonesia. Semarang City has 26 hospitals of various types and categories. Data on these hospitals were obtained from the official website of Semarang City [28]. Out of the 26 hospitals in Semarang City, 10 hospitals will be selected as samples. The sampled hospital locations are distributed across densely populated areas within the city. A map illustrating the distribution of hospitals and routes between hospitals is presented in Figure 1.



Legend:

Node	Hospital Name
10	RSD KRMT Wongsonegoro
20	RS Panti Wilasa Citarum
30	RSND Undip
40	RS Telogorejo
50	RS St. Elisabeth
60	RS Roemani
70	RS Islam Sultan Agung
80	RS Bhayangkara Majapahit
90	RSJD Amino Gondohutomo
100	RSUP Dr. Kariadi

Figure 1: Map of Hospital Distribution and Travel Routes

Traffic data were obtained from Google Maps Traffic using the Google Maps API, which provides estimated travel times in minutes. Various travel routes between hospitals were also sourced from Google Maps, with at least three alternative routes suggested for each hospital connection. All alternative routes between hospitals were then developed into a graph network, where each intersection was identified as a node, and the paths connecting these nodes were designated as edges. Additional nodes and edges were integrated along adjacent paths in all alternative routes to increase the complexity of the graph network, thereby expanding the number of potential alternative routes. The coordinate points of each hospital were also designated as nodes. Data from Google Maps Traffic included estimated travel times (in minutes) from one node to another.

Road condition data for Semarang City were obtained from the official website of the Semarang City Government [27]. The road condition data used in this study include 1) road width (meters), 2) road segment length (meters), and 3) percentage of road damage. These road condition data and the estimated travel time (minutes) influence the weight of road edges. All data were subsequently compiled and tabulated into a dataset, as shown in Table 1.

Table 1: Research Data

No	Street Name	Origin Street (Node)	Origin Coordinates	Destination Street (Node)	Destination Coordinates	Travel Time (minutes)	Road Width (meters)	Road Section Length (meters)	Road Condition (%)
1	Agus Salim	Pemuda **(1)**	-6.971054, 110.422868	Empu Tantular **(2)**	-6.971368, 110.425703	1	16	320	80.53
2	Agus Salim	Empu Tantular **(2)**	-6.971368, 110.425703	Bunderan Museum Kota Lama **(3)**	-6.969883, 110.430618	2	16	550	80.53
3	Agus Salim	Bunderan Museum Kota Lama **(3)**	-6.969883, 110.430618	Pemuda **(1)**	-6.971054, 110.422868	3	16	950	80.53
4	Ahmad Dahlan	Simpang Lima **(5)**	-6.989623, 110.423904	Gang Seroja I **(157)**	-6.988119, 110.426898	1	8	400	100.00
...	...	...	...	...	...	...	...	...	...
348	Wonodri Sendang Raya	Sriwijaya **(61)**	-7.001639, 110.427488	Wonodri Baru Raya **(166)**	-7.003744, 110.426282	1	3.5	300	75.00
...	...	...	...	...	...	...	...	...	...
363	Yos Sudarso	Puteran Yos Sudarso / Kaligawe Raya **(149)**	-6.952555, 110.450569	Kaligawe Raya **(96)**	-6.956678, 110.451760	2	10	515	90.00

From the research data, which consists of 363 rows representing origin and destination node pairs, several observations can be made:

1. Travel Time: The average travel time between intersections is 2.11 minutes, with a minimum of 1 minute and a maximum of 9 minutes. The travel time estimates obtained from Google Maps consistently indicate a minimum value of 1 minute, even for the shortest distances. In this instance, the shortest distance recorded is 31 meters, specifically from node 28 to node 43.
2. Road Width: The average road width is 10.12 meters, with a range spanning from 3 meters to 20 meters. Roads that are less than 5 meters wide are classified as village roads, while those wider than 5 meters are categorized as city roads, provincial roads, national roads, and toll roads.
3. Length of Road Segments: The average length of road segments is 779.26 meters, with a minimum of 31 meters and a maximum of 7203 meters. The distances between nodes exclusively determine this variation and do not correlate with road classifications such as village roads, city roads, provincial roads, national roads, or toll roads.
4. Road Condition: The average road condition is recorded at 95.34%, with the poorest condition documented at 60% and the best at 100%. A good road condition is characterized by a smooth, even surface free from undulations or potholes. In contrast, a poor road condition features uneven surfaces, undulations, and the presence of potholes, which can compromise the comfort and safety of road users.

Method

This research focuses on modifying the A* and Bellman-Ford algorithms to determine the shortest travel route for ambulances while considering patient safety factors during transit. Each algorithm will be tested in two variants: the primary and modified algorithms. The basic algorithm utilizes only the weight of the travel distance. In contrast, the modified algorithm also incorporates the road's width and the road's quality as total weights in determining the travel route. The weight calculation criteria for both modified algorithms remain the same. Although we have travel time data obtained from Google Maps Traffic, travel time is not included as a parameter in the weight for route searching. This is due to the nature of the travel time data from Google Maps Traffic, which provides estimated travel times rather than actual travel times. Google Maps always assigns a minimum travel time of one minute for any road segment, even for very short distances.

In the A* algorithm, a heuristic function estimates the initial weight; therefore, a heuristic function will be added to both the primary and modified algorithms. Two variations of modification will be applied to the A* algorithm: modifications to the weights and modifications to the heuristic function. The heuristic function employed is the Haversine heuristic, which considers the estimated geographical distance. Modifying the heuristic function in the A* algorithm involves adding an estimated travel time. This addition ensures that the A* algorithm considers travel time when determining the route, producing a more optimal route. Since the Bellman-Ford algorithm does not utilize a heuristic function, only weight modifications will be applied to the Bellman-Ford algorithm.

*1) A*Algorithm*

a. The general model of the A* algorithm function ($f(v)$) is presented as follows:

$$f(v) = g(v) + h(v) \tag{1}$$

where:

$g(v)$ = The total weight function (W) from the initial node to node (v) is defined, where the weight in this context represents the travel time between nodes.

$h(v)$ = The heuristic function calculates the estimated geographical distance (d) from node (v) to the goal node ($goal$) using the Haversine formula [29].

$$h(v) = 2r.\,arcsin\left(\sqrt{sin^2\left(\frac{\Delta lat}{2}\right) + cos(lat_1).\,cos(lat_2).\,sin^2\left(\frac{\Delta lon}{2}\right)}\right) \tag{2}$$

b. The A* algorithm is modified by adjusting the heuristic function to include an estimate of travel time (t).

$$h(v) = t(v, goal) + \frac{haversine(v,goal)}{1000} \tag{3}$$

Here ($t(v, goal)$) represents the estimated travel time (t) from node (v) to the goal node ($goal$).

c. Furthermore, the A* algorithm is enhanced by modifying the weights to incorporate road width and road quality as parameters in determining the travel route.

The weight modification is carried out by incorporating all parameters to adjust the weight values for each edge in the graph. Since the previous function was defined as $g(v) = W$ (where (W) represents the total weight function), the introduction of additional parameters leads to a change in the total weight (W) to the modified weight (W_M). This modification occurs because the total weight is now influenced not only by the length of the road segment (W_D) but also by the road width (W_w) and the road condition (W_Q).

The modified weight (W_M) is now altered to reflect these changes:

$$W_M = W_D \,.\, W_w \,.\, W_Q \tag{4}$$

$$W_D = \frac{D}{1000} \tag{5}$$

where D is the length of the road segment (meters)

$$W_w = 1 + \frac{width\_adjustment}{5} \tag{6}$$

where $width\_adjustment$ define:

$$width\_adjustment = \begin{cases} \infty, & if\ \ w < 4\ \ and\ \ D \geq 300 \\ \frac{1}{max\left(1, \frac{w}{10}\right)}, & else \end{cases} \tag{7}$$

with w is road width (meters) and D is length of road section (meters)

$$W_Q = 1 + \frac{road\_quality\_adjustment}{5} \tag{8}$$

where $road\_quality\_adjustment$ define:

$$road\_quality\_adjustment = 1 - \left(\frac{Q}{100}\right) \tag{9}$$

with Q is quality of road section (%)

Equation (5) presents the calculation of the distance weight (W_D), which will influence the overall value of the Modified Weight (W_M). A divisor of 1000 is employed to convert the distance value into kilometres. The Modified Weight (W_M) will be directly affected by the distance weight (W_D), as the travel distance is the primary weight that impacts the A* Algorithm in generating the shortest route.

Equation (6) demonstrates that the value of the road width weight (W_w) will be infinite (∞) if the width of the road (w) to be traversed is less than 4 meters, and the length of the road segment (D) is greater than or equal to 300 meters. The value of (W_w) becomes infinite (∞) because the $width\_adjustment$ value generated by Equation (7) is infinite (∞). An infinite value (∞) of (W_w) will result in the road segment not being selected as a travel route. In Equation (7), if the conditions of the road width (w) being less than 4 meters and the length of the road segment (D) being greater than or equal to 300 meters are not met, then the $width\_adjustment$ value follows the formula $\frac{w}{10}$ with a maximum $width\_adjustment$ value of 1. The divisor of 10 is a fair number derived from the average value of all road width data. The combination of the parameters of road segment length and road width is utilized as one of the parameters because these two conditions can directly influence the estimated travel time. As explained in the introduction, the ambulance (EV) is expected to reach the location in the shortest possible time. Narrow roads accompanied by long road segments significantly affect the likelihood of traffic congestion. The values of 4 meters for road width and 300 meters for road length are chosen as moderate values, considering the dimensions of typical ambulance vehicles, which need to be able to pass other vehicles when traversing specific road segments to find the shortest route. Wider roads are expected to maximize travel time efficiency. Shorter travel times indicate that the vehicle is moving at higher speeds. According to the operational regulations for emergency vehicles, the speed of EVs is limited to a maximum of 40 km/h in urban areas and 80 km/h on highways to ensure patient safety [30].

Equation (8) illustrates the calculation of the road quality weight (W_Q), where the best road quality (Q), valued at 100, results in a $road\_quality\_adjustment$ of 0. With a $road\_quality\_adjustment$ value of 0, the road quality weight (W_Q) will equal 1, thereby rendering (W_Q) ineffective in influencing the Modified Weight (W_M). As the road quality deteriorates, the $road\_quality\_adjustment$ value increases, leading to a corresponding increase in the road quality weight (W_Q). The condition of the road quality (degree of road damage) significantly impacts the safety and security of patients during transit, particularly for critically ill patients.

2) Bellman-Ford Algorithm

a. The general model of the Bellman-Ford algorithm function ($d(v)$) is presented as follows:

Initialization:

$$d(v) = \begin{cases} 0, & if \ \ v = start\ node\ (origin) \\ \infty, & if \ \ v \neq start\ node\ (origin) \end{cases} \tag{10}$$

where $d(v)$ represents the shortest distance from the source node to node v.

Edge relaxation is performed for each edge (u, v, w), where: u is the starting node, v is the ending node, and w is the weight of the edge between u and v.

$$d(v) = min\{d(v), d(u) + w\} \tag{11}$$

This means that the distance from the source to node v will be updated if passing through u provides a shorter distance.

b. The Bellman-Ford algorithm is modified by incorporating road width and road quality as weight parameters in determining travel routes.

The modified weight W_M used in the Bellman-Ford algorithm is consistent with that employed in the A* algorithm. The modified weight equations follow equations (4) to (9). With the addition of the modified weight, the relaxation equation of the Bellman-Ford algorithm, as represented in equation (12), is altered to:

$$d(v) = min\{d(v), d(u) + W_M\} \quad (12)$$

The routes generated by all algorithm variations will be compared against the travel routes provided by Google Maps, which includes comparisons of travel distance, estimated travel time, and the routes generated to evaluate the performance (accuracy) of each algorithm variation about Google Maps [21]. The travel distance and estimated travel time are calculated based on the actual distance and time from the starting node to the final destination according to the dataset after the shortest travel route has been successfully identified by each algorithm variation. The results of this comparison are presented in a boxplot graph, which is then interpreted and analyzed to conclude.

RESULTS

The first task involves executing each algorithm to determine the travel routes between 10 hospitals. From these 10 hospitals, origin and destination node pairs are created, resulting in 90 origin-destination node pairs representing the source and destination hospitals. Upon running the algorithms, data on travel routes, distances, and travel times will be obtained for each of the 90 origin-destination pairs. The next step is to compare the travel distance data from the routes generated by the experiments using five algorithms against the travel distances provided by Google Maps. The five algorithms being compared are: A* Algorithm with Haversine Heuristic (A*-HH), Bellman-Ford Algorithm (BF), A* Algorithm with Modified Haversine Heuristic Weights (A*-HHWM), A* Algorithm with Modified Heuristic and Modified Weights (A*-HMWM), and Bellman-Ford Algorithm with Modified Weights (BF-WM).

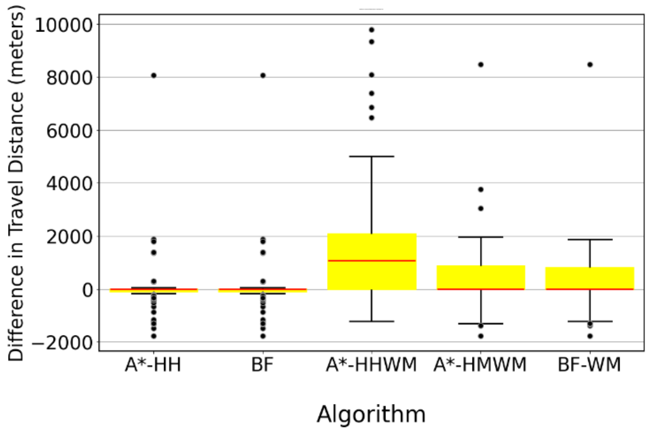


Figure 2. Graph of the differences in travel distance among various models of the A* and Bellman-Ford algorithms compared to Google Maps

The boxplot presented in Figure 2 illustrates the comparison of travel distance differences generated by five algorithms (A*-HH, Bellman-Ford, A*-HHWM, A*-HMWM, and BF-WM) against the travel distance provided by Google Maps. Based on the boxplot, it can be observed that A*-HH and BF exhibit a distribution of distance differences that is very close to zero, with travel distances being highly uniform. This uniformity is influenced by the fact that the routes produced by both algorithms are very similar. Both algorithms show minimal or almost insignificant differences compared to Google Maps, as evidenced by the median being nearly aligned with zero.

Upon closer examination, the interquartile range and whiskers of A*-HH and BF predominantly lie below zero, although still around zero, indicating that most of the travel distances generated by these two algorithms are shorter than those from Google Maps, albeit not significantly. The A*-HHWM algorithm demonstrates a much more extensive range of distance differences than the other four algorithms. The median, which is significantly above zero (around 1000 meters) and an interquartile range above zero, suggests that the A*-HHWM algorithm tends to produce greater travel distances than Google Maps.

The A*-HMWM and BF-WM algorithms exhibit a wider distribution of distance differences than A*-HH and BF, but not as extensive as A*-HHWM. With interquartile ranges for these three algorithms all above zero, it indicates that most routes generated result in longer travel distances than those from Google Maps. The number of routes with longer travel distances produced by A*-HMWM and BF-WM is fewer than those generated by A*-HHWM, as reflected by the narrower interquartile ranges and whiskers of the A*-HMWM and BF-WM algorithms compared to A*-HHWM. A more detailed observation reveals that BF-WM has a lower interquartile range than A*-HMWM, although the difference is insignificant. The medians of both algorithms remain close to zero, but several notable outliers are present.

Based on the distribution of travel distance differences from the 90 routes generated by the five algorithms, the A*-HH and Bellman-Ford algorithms produced over half of the travel routes with identical distances to those provided by Google Maps, with 29 routes showing negative distance differences and 12 routes showing positive differences. The A*-HHWM algorithm generated more than 60% of the travel routes with positive distances, with 15 routes identical to Google Maps, while the remaining routes had negative distances. The A*-HMWM and BF-WM algorithms exhibited similar characteristics, with 16 and 18 routes resulting in negative distances, respectively. Conversely, the proportion of positive distances and distances identical to Google Maps ranged from approximately 35% to 45%. Overall, the A*-HH and Bellman-Ford algorithms achieved a travel distance accuracy of 96.38%, while the A*-HHWM algorithm demonstrated an accuracy of 79.83%. The A*-HMWM and BF-WM algorithms achieved accuracies of 90.92% and 92.58%, respectively. A comparative accuracy graph of travel distances between the various A* and Bellman-Ford algorithm models against the travel distances provided by Google Maps is shown in Figure 3.

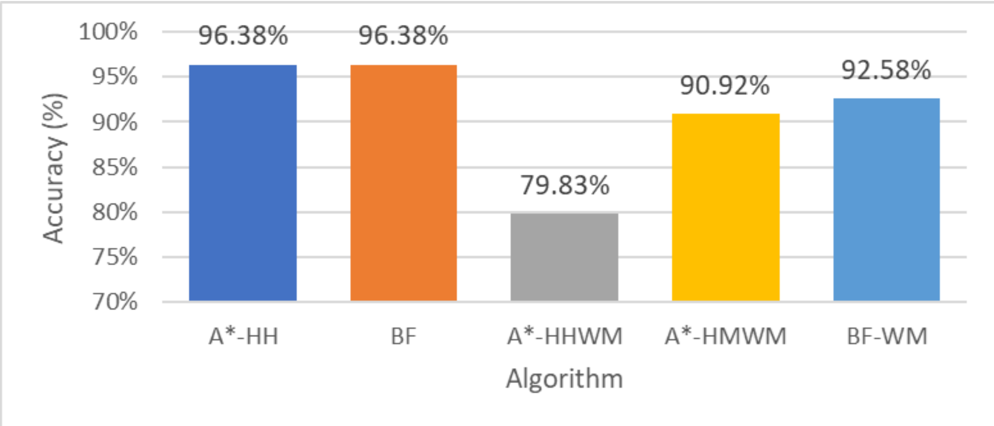


Figure 3. Comparison chart of travel distance accuracy between various A* and Bellman-Ford algorithm models and Google Maps

Based on the boxplot analysis and the distribution of travel distance accuracy across the 90 routes generated by the five algorithms, it is evident that the A* and Bellman-Ford algorithms exhibit the same level of accuracy when route selection is influenced solely by travel distance. This is attributed to the identical data distribution for all travel routes produced by both algorithms. However, when route selection is also influenced by road width and road quality conditions, it becomes apparent that the Bellman-Ford algorithm (BF-WM) demonstrates superior travel distance accuracy compared to the A* algorithm (A*-HHWM). The travel distance accuracy of the A* algorithm (A*-HHWM) significantly decreases compared to the scenario where route selection is influenced only by distance (A*-HH).

The performance accuracy of the A* algorithm on routes that are affected by road width and quality conditions is notably improved through modifications to the haversine heuristic function by incorporating estimated travel time into the heuristic function (A*-HMWM). Following the modification of the heuristic function, the travel distance accuracy of the A* algorithm (A*-HMWM) approaches that of the Bellman-Ford algorithm (BF-WM), with a difference of only 1.66%. However, it remains below that of Bellman-Ford (BF-WM).

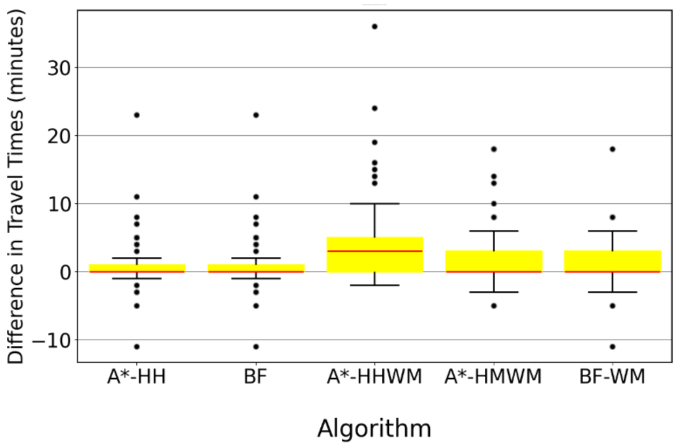


Figure 4. Graph of travel time differences among various A* and Bellman-Ford algorithm models compared to Google Maps

Figure 4 illustrates the boxplot of travel time differences among various variations of the A* and Bellman-Ford algorithms compared to the travel times generated by Google Maps. From this boxplot, it is evident that the A*-HH and Bellman-Ford algorithms display identical visualizations, attributed to the fact that all travel routes produced by these two algorithms have the same data distribution. The A*-HH and Bellman-Ford algorithms exhibit a more minor data variation than the others, as indicated by their narrower interquartile ranges and whiskers. The medians, closely aligned with zero, suggest that most travel times generated by these algorithms are consistent with those of Google Maps.

The A*-HHWM algorithm, on the other hand, has the broadest interquartile range among the other algorithms, indicating the highest variation in travel times compared to the others. The median above zero suggests that A*-HHWM has more discrepancies in travel times than Google Maps. The boxplots of the A*-HMWM and BF-WM algorithms exhibit similar characteristics, with slight differences in outliers. A*-HMWM and BF-WM show more minor variations than A*-HHWM, yet still more significant than those of A*-HH and Bellman-Ford. This is reflected in their interquartile ranges, which are narrower than A*-HHWM but broader than those of A*-HH and Bellman-Ford. The medians, either aligned with or very close to zero, indicate that nearly all travel times produced by these two algorithms are comparable to those of Google Maps. The interquartile ranges of the five algorithms lie above zero, suggesting that there are more instances of longer travel times compared to Google Maps than shorter travel times.

The travel time data from the 90 routes generated by the five algorithms indicate that the A*-HH, Bellman-Ford, and BF-WM algorithms have travel times more consistent with Google Maps. The A*-HMWM algorithm produced nearly half of its 90 routes with travel times matching those of Google Maps. In contrast, A*-HHWM exhibited a significantly higher number of travel time discrepancies compared to Google Maps. The A*-HH and Bellman-Ford algorithms achieved the highest travel time accuracy at 94.04%, while A*-HHWM had the lowest accuracy at 79.70%. The A*-HMWM and BF-WM algorithms demonstrated relatively close travel time accuracies of 87.66% and 91.91%, respectively. A comparison chart of travel time accuracy between various A* and Bellman-Ford algorithm models and the travel times provided by Google Maps is presented in Figure 5.

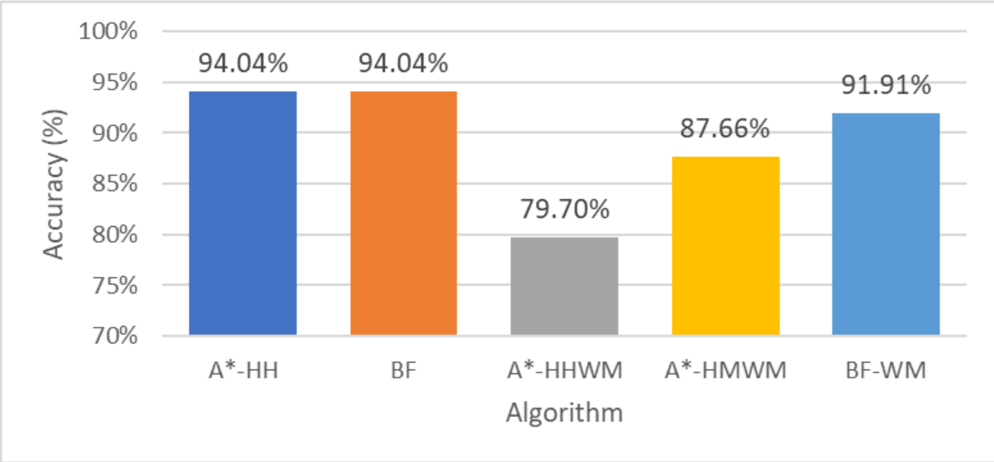


Figure 5. Comparison chart of travel time accuracy between various A* and Bellman-Ford algorithm models and Google Maps

Based on the analysis of the boxplot and travel time accuracy across the 90 routes generated by the five algorithms, both the A* and Bellman-Ford algorithms exhibit the same level of accuracy when route selection is influenced solely by travel distance. This similarity in accuracy is due to the identical data distribution between the two algorithms for all travel routes. When route selection is also affected by road width and road quality conditions, it is evident that the Bellman-Ford algorithm (BF-WM) demonstrates better travel time accuracy than the A* algorithm (A*-HHWM). The travel time accuracy of the A* algorithm (A*-HHWM) is significantly improved following modifications to the haversine heuristic function (A*-HMWM). The difference in travel time accuracy between the A* algorithm (A*-HMWM) and the Bellman-Ford algorithm (BF-WM) is reduced to 4.25%, down from a previous difference of 12.21%.

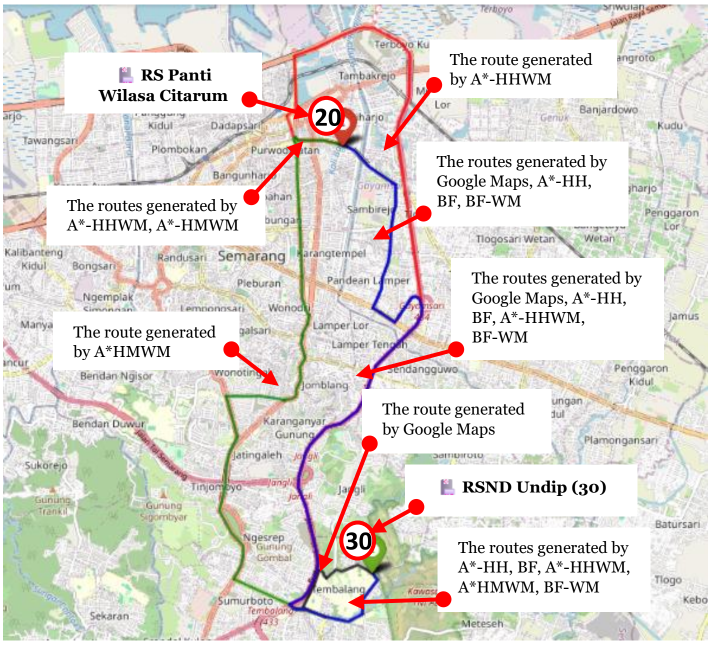


Figure 6. Comparison of travel routes from RSND Undip (node 30) to RS Panti Wilasa Citarum (node 20) for A*-HH, BF, A*-HHWM, A*-HMWM, BF-WM algorithms, and Google Maps

Figure 6 illustrates the comparison of travel routes generated by the five algorithms (A*-HH, BF, A*-HHWM, A*-HMWM, and BF-WM) and Google Maps from RSND Undip (node 30) to RS Panti Wilasa Citarum (node 20). Three algorithms (A*-HH, BF, and BF-WM) produced identical routes. These three algorithms, along with Google Maps, partially utilized toll roads (purple route) and partially non-toll roads (blue route). However, a slight difference in route selection occurred when departing from RSND Undip: Google Maps opted for the route through node 39 (black route), whereas the three algorithms selected the route via node 47. Google Maps resulted in a longer distance but offered a shorter estimated travel time than the three algorithms, which provided a shorter route with a longer travel time. The difference in travel time between these two routes was 1 minute, while the distance difference was 800 meters. The A*-HHWM algorithm exclusively selected toll roads (red and purple routes) with a travel distance of 20.5 km and an estimated travel time of 41 minutes. This is 10 minutes slower and 4.3 km longer than the route provided by Google Maps. Conversely, the A*-HMWM algorithm selected a route that avoided toll roads entirely (green route). This route was 400 meters shorter than Google Maps but had a travel time that was 9 minutes longer.

DISCUSSION

In line with the research focus on developing algorithms for ambulance navigation while ensuring patient safety during transit, it was observed that the Bellman-Ford and A* algorithms successfully avoided the route used by Google Maps when traveling from node 30 (RSND Undip) to node 60 (RS Roemani). This route included a narrow road (3.5 meters wide) with a road quality rating of 75%, specifically on the segment between nodes 61 and 166. This segment, a rural road with limited width, is prone to congestion and poses a heightened risk of exacerbating patient injuries due to its poor condition. The road's considerable length and low quality resulted in a high weight modification (WM) within the Bellman-Ford and A* algorithms, excluding this road segment from their route options. Instead, alternative routes were selected to mitigate the adverse effects of ambulance transit on patients [16], [18], [19]. The Bellman-Ford algorithm (BF-WM) and the A* algorithm (A*-HMWM) were designed to prioritize the shortest possible ambulance travel routes while emphasizing patient safety and security.

Table 2 presents the state of the art in research compared to other studies. Previous research focused solely on finding the shortest route. At the same time, our study aims to identify the fastest route while avoiding potential congestion and damaged roads to ensure the safety and security of patients from more severe injuries during transit. As outlined in the introduction, the urgency of ambulance travel is to reach the destination quickly via the shortest route to safeguard patient safety. In this context, short travel distance, brief travel time, and the patient's condition are the primary factors of concern.

Table 2: Research Development and Innovations

References	Data	Method	Research differences	Results
[20]	roads photos taken using CCTV or drones after a natural disaster	combining the shortest path algorithm with and real-time VGG19 Convolutional Neural Network (CNN)	focuses on real-time road damage classification detection accuracy than finding the shortest route	accuracy of road damage classification detection: 98%
[21]	road density and segment length	Fuzzy Sugeno-Dijkstra	shortest route search, accuracy of distance compared to Google Maps	distance accuracy: 86,72%
This research	estimated travel time, segment length, road width, and road quality	A*-HMWM (heuristic modified and weight modified) dan BF-WM (Bellmab-Ford with weight modified)	shortest route search, avoiding damaged roads and high-congestion roads, distance accuracy, and travel time accuracy compared to Google Maps	**A*-HMWM:** distance accuracy: 90.92%, travel time accuracy: 87.66% **BF-WM:** distance accuracy: 92.58%, travel time accuracy: 91.91%

The performance testing results for the accuracy of the modified A* algorithm (A*-HMWM) and the modified Bellman-Ford algorithm (BF-WM) compared to Google Maps indicate that both algorithms achieve travel distance accuracies of 90.92% and 92.58%, respectively, which are higher than the accuracy reported by Al Mustafid et al., which was 86.72% [21]. The travel time accuracy performance of the modified A* algorithm (A*-HMWM) and the modified Bellman-Ford algorithm (BF-WM) is also notably high, at 87.66% and 91.91%, respectively, compared to Google Maps, while still maintaining routes that avoid damaged roads and potential congestion. This research also proves that the Bellman-Ford algorithm performs slightly better than the A* algorithm, even though it executes slower [26].

CONCLUSIONS

Based on the analysis of both algorithms, A* (A*-HMWM) and Bellman-Ford (BF-WM), it was found that the Bellman-Ford algorithm exhibits slightly better accuracy compared to the A* algorithm. However, the A* algorithm presents more significant potential for development due to its flexible heuristic function. By appropriately modifying the heuristic function, the accuracy of the A* algorithm can be enhanced for various conditions.

When implementing algorithms to avoid narrow and damaged roads, both algorithms successfully provided navigation routes for ambulances while prioritizing patient safety. Both algorithms effectively avoided the edge connecting nodes 61 and 166, which spans 300 meters with a road width of 3.5 meters and a road condition quality of 75%. This segment was avoided because damaged road conditions could exacerbate vibrations and shocks, potentially worsening the patient's condition.

The high accuracy of both algorithms demonstrates their potential for further development into real-time navigation systems that can adapt to changes in dynamic road congestion. This adaptability is essential given the potential for sudden traffic changes due to extraordinary events such as accidents or other emergency vehicle operations that may obstruct ambulance routes.

In this study, road damage conditions influenced route selection moderately, primarily based on the extent of road damage. Future research could evaluate the threshold percentage of road damage that ambulances should avoid to optimize route-finding algorithms, ensuring maximum patient safety and comfort.

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