IJIRMET ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
Vol. 7, Issue 3, March 2022

ANN Based E-Commerce Distribution Optimization Of Rice Agricultural Products Based On Consumer Satisfaction

[1] Dr. C. Dhaya, Ph.D,[2] Mr. K. Prasannakumar M.E.,[3] Ahila.P

[1] Head Of the Department, Department of Computer Science and Engineering, Adhiparasakthi Engineering College, Melmaruvathur, Tamilnadu, India.

[2] Assistant Professor, Department of Computer Science and Engineering, Adhiparasakthi Engineering College, Melmaruvathur, Tamilnadu, India.

[3] Department of Computer Science and Engineering, Adhiparasakthi Engineering College, Melmaruvathur, Tamilnadu, India.

Abstract: The purpose of this study is to expect the net income extent for natural merchandise, pick out vital elements for promoting natural merchandise, and advise internet advertising techniques for natural product income. Through the evaluation of natural merchandise on Taobao's platform, the emotional evaluation technique is used to divide the evaluation of crawling natural merchandise into fantastic evaluations and poor evaluations. Using the Latent Dirichlet Allocation (LDA) technique, extracting keywords, figuring out vital elements for promoting natural merchandise, the use of online survey techniques and regression evaluation techniques, acquiring customers' buy intentions, and suggesting internet advertising techniques for natural product income, and with the aid of using gathering statistics on natural merchandise' rate, modern rate, loose shipping, income extent, variety of patron evaluations, patron evaluations, natural labelling, and product enthusiasts on Taobao's platform, the neural community evaluation technique is used to are expecting the net income extent for natural merchandise. This has a look at determined that packaging design, dietary information, meals quality, shipping hazard, freshness, and supply hazard are the vital online elements with inside the shopping for of natural merchandise, and the merchandise' enthusiasts, rate discount, and numerous patron evaluations affected the income extent. Therefore, the merchandising of online offerings and logistics may be used to grow the income of natural merchandise. This study has a vital function in selling the sale of natural merchandise and enhancing customer satisfaction, imparting customers with secure and dependable merchandise, and on the equal time has vital importance for selling sustainable development.

Keywords— artificial neural network; route-planning system; machine learning; A-star; shortest-path model.

1. INTRODUCTION

Currently, Industry 4.0 technology has the capability to have an effect on the operations of many industries. As proven in Figure 1, big data analytics and self-reliant robots are the two vital components of Industry 4.0 technology [1]. Autonomous robots are an increasing number of used to automate ordinary responsibilities in lots of commercial programs and responsibilities in unique regions which can be dangerous to operators. Artificial intelligence (AI)-primarily based totally automation is adaptive and has many realistic programs in exclusive industries. The transportation enterprise is one of the regions which have the capacity for the utility of AI-primarily based totally automation, specially in delivery chains, in which there are big quantities of transactional facts at each stage. As such, the strategies worried can obtain blessings from AI and robotics automation. The development of AI and robotics technology brings approximately new possibilities for enhancing operations throughout a delivery chain. With AI and robotics automation, groups can gather and carry out facts evaluation autonomously, which improves delivery chain responsiveness. Breakthroughs in AI, robotics, and automation can boost up fabric development, the go with the drift of products, fabric handling, and exceptional manipulation in an incorporated environment. The performance of operations inside a warehouse may be progressed with the utility of AI-primarily based totally automation because of the excessive prices of motion of products. One of the well-known warehouse robotic structures is the Kiva device applied at Amazon. The device became used to enhance the performance of warehouse operations.

Copyright to IJIRMET

Figure 1. Industry 4.0 technology [1].

II. OBJECTIVES

The purpose of this study become on growing an AI-primarily based totally automation method for controlling the motion of automatic cars inside a warehouse. In a regular operation inside a warehouse, the quantity of everyday product motion is huge, and, in general, the routes are decided primarily based totally on the revel in of drivers. Dynamic hurdles can hinder the motion via a few direction segments inside a warehouse and will have an effect on the routes that may be utilized by the drivers. A path-making plans method with the attention of dynamic hurdles is complicated and can't depend most effectively on the human revel in. In this study, methodologies for figuring out routes that keep in mind real-time boundaries are offered. The methodologies encompass an optimization version for routing decisions, an A-star heuristic method, and machine learning models primarily based totally on artificial neural networks (ANN). The novelty of this studies may be summarized as follows:

• This study provides a path-making plans method primarily based totally on an ANN. The ANN may be applied on automatic guided cars (AGVs) with confined computing resources. Once an ANN is trained, it is able to generate a path with minimum computational attempt and runtime (much less than a second).

• The taken into consideration path-making plans trouble is primarily based totally on realistic warehouse surroundings that consider real-time boundaries. • A path-making plans machine that collects the facts for education an ANN and generates routes primarily based totally on real-time positions of boundaries is introduced.

• The proposed method is adaptive and scalable. It may be carried out to different routing issues with specific requirements. Heuristic techniques may be used for producing routes for large-scale issues.

• This study provides managerial insights into how the configuration of an ANN influences the accuracy and the way the quality configuration may be chosen. The organization of this paper is as follows: Section II provides a literature review associated with movement-making plans and path making plans. A mathematical version for routing selections and an A-star heuristic are defined in Section III. An ANN version for dynamic path-making plans is offered in Section IV. The transportation surroundings used in this study are offered in Section V. A dynamic routing machine and computational effects with managerial insights are offered in Section VI. The conclusions and viable destiny studies are mentioned in Section VII.

III. LITERATURE REVIEW

The making plans of self-reliant motion of a robot is associated with foremost areas, the motion plans, and route (or path) making plans. A literature review of key articles and the studies hole are furnished in this section.

A. MOTION PLANNING

When making use of motion planning to the self-sustaining motion of a robot, the intention is to decide a chain of movement that actions the robotic from an origin to a destination. In trendy, motion planning has impediment collision avoidance capability, the use of to be had records from specific geared up sensors to navigate the robotic through controlling the velocity and path of motion. A-start algorithm has been implemented to many movements making plans troubles and is taken into consideration one of the maximum famous algorithms.

Liu and Gong [4] implemented many versions of the A-start algorithm for route making plans for a rescue robotic operation. They offered many versions of the A-famous person set of rules in step with the complexity of the rescue surroundings, in addition to the precision of the sensors. Because of the noise from the indicators detected through the robotic, approximated records of the robotic's orientation are required. El Halawany et al. [5] said that A-famous person is the first-class trendy set of rules for attempting to find the most efficient route. Motion planning is used in lots of varieties of applications, mainly in synthetic intelligence-associated areas. Contreras-González et al. [6] advanced an ANN to expect the vicinity of an AGV through the use of operational records containing the accuracy from the version and the real vicinity of the AGV. The proposed ANN version should generate a clean and correct factor-to-factor tour plan in the area checking out without managed surroundings. Zhang et al. [7] proposed an improved A-start algorithm for directing an automatic guided car (AGV). The proposed technique should generate green paths that lessen superfluous inflection points and redundant nodes. Gochev et al. [8] proposed the combination of a collision-avoidance technique and the A-start algorithm in surroundings with specific retailers for an AGV system. In the experiment, the AGVs needed to observe specifically assigned paths without colliding with the boundaries. Mohan and Ignatious [9] studied the software of a cell robotic in warehouse surroundings with the tracking of battery health. An improved A-start algorithm became used to generate the trails for robots. Kurdi et al. [10] advanced an smart controller for route making plans the use of an ANN. The authors-built collision-loose paths for transferring robots amongst boundaries primarily based totally on more than one input from specific resources.

Zhang et al. [11] proposed an ANN version for route management of an AGV that considers the line-of-sight at some stage in motion in unfavorable conditions. Flórez et al. [12] advanced a manage method for an AGV. A hybrid kinematic controller became advanced primarily based totally on a mixture of a developed ANN and a genetic set of rules. The controller became used to govern automobile kinematics to keep away from boundaries. From the take a look at results, the car reached a positive stage of autonomy, in step with a controller that took under consideration the kinematics and dynamics of the system. A new counseled technique that mixed the A-star set of rules and motion planning plans, and that would discover an international route, tune the route, and keep away from collisions in dynamic surroundings, in addition to in a static one, became added through Zhong et al. [13]. For real-time boundaries, route-making plans with A-star generated an international route that stored a distance from the boundaries; the route became tracked with a window adaptive method that helped the robotic tune the complete route easily and attain the very last intention without collisions.

B. ROUTE PLANNING

Bhadoria and Singh [14] confirmed that algorithms inclusive of Dijkstra and A-start may be carried out for each direction making plans and routing decisions. Many eventualities had been created primarily based totally on an unstructured and unpredictable environment, wherein the robots had been pressured to stand new conditions wherein decision-making turned into pretty troublesome. Zhang and Zhao [15] took into consideration an incorporated framework for combining A-start and a Dijkstra algorithm. The proposed algorithm turned into used to manual a cell robotic alongside the direction among a foundation and a supplied vacation spot with the cap potential to keep away from collisions with hurdles. Kusuma and Machbub [16] applied an A-start algorithm for making plans for the motion of a humanoid robotic. The proposed algorithm ought to discover a new direction if the vacation spot turned into changed or if the robotic did not observe the assigned direction. Ruiz et al. [17] took into consideration an open car routing trouble with ability drawback and distance constraints. A biased random-key genetic algorithm designed to clear up the trouble turned into benchmarked with 3 datasets to illustrate the performance of the proposed algorithm. Salavati-Khoshghalb et al. [18] investigated a car routing trouble (VRP) that took into consideration uncertainty in call for a restocking policy.

An integer L-formed set of rules and numerous decrease certain schemes have been advanced to decide the answers for issues with as many as 60 clients and 4 vehicles. Zhang et al. [19] studied an ant colony optimization algorithm for a multi-goal automobile routing trouble with bendy time windows. The version aimed to concurrently reduce the overall distribution fees and maximize the general purchaser satisfaction. Sung et al. [20] advanced a neural community that might be used to decide a collision-loose route in large-scale dynamic surroundings generated from a dataset that become extracted from a Bellman-Ford algorithm and a quadratic program. The dataset from the Bellman-Ford algorithm confirmed higher reliability for schooling the neural community because of the appropriateness of this algorithm in a discretized space. Pasha et al. [21] formulated a mixed-integer linear programming version for an open capacitated VRP with gentle time windows. An optimization version and 4 metaheuristic algorithms have been advanced to remedy the trouble. The effects have proven that the evolutionary algorithm supplied good-pleasant answers for each the small-scale and the large-scale issues with realistic runtime. Trachanatzi et al. [22] addressed an environmental prize-amassing automobile routing trouble. A firefly algorithm primarily based on coordinates (FAC) become designed to remedy the version. The proposed set of rules become carried out and examined many times from preceding research to illustrate the promising overall performance of the FAC. A precis of the strategies utilized in key associated articles are proven in Table 1.

According to the literature review, route-planning and path issues for AGV are energetic studies regions associated with Industry 4.0 technology. None of the studies addressed an adaptive answer method for route-planning trouble inside a warehouse that considers real-time obstacles. The gift studies centered on growing an answer method the usage of ANN for route-planning problem trouble with real-time obstacles. A dynamic direction-making plans device is likewise proposed. The fundamental contribution of this study is the improvement of a green direction-making plans method the usage of a gadget gaining knowledge of version that may be carried out on AGVs with restrained computing resources. An ANN version that may be used to decide the parameters that designate the connection among the input and output of dynamic route-planning trouble is introduced. This can then be carried out to expect the direction primarily based totally on exclusive situations of input data.

IV. MODELS AND ALGORITHMS FOR ROUTE PLANNING

To decide an answer for a route-planning problem, each an optimization version and a heuristic set of rules had been used. In this section, a shortest-direction version is brought and used as a benchmark for trying out the best of answers from different methods. A heuristic technique primarily based totally on an A-star algorithm is provided next.

A. HEURISTIC ALGORITHM FOR PATH PLANNING (A-STAR ALGORITHM)

In this study, an A-star algorithm was used to identify a path that avoids obstacles on any path segment. The algorithm can be described as follows:
During the path search of an A-star algorithm, an "OPENED" list and a "CLOSED" list are used to keep track of information during the search. The "OPENED" list stores the paths that will be explored. The "CLOSED" list contains all explored paths. Let h(n) represent the cost from an origin to the current node (n) and let g(n) represent the cost to get from the current node (n) to a destination node. The total cost, f (n), is calculated for each successor node that includes both h(n) and g(n). The procedure consists of seven steps [24]:

1. The start node is removed from the "OPENED" list. The cost function f(n) is calculated; note that h(n) = 0 and g(n) are calculated on the basis of the distance between the start position and the destination (f (n) = g(n)).
2. A node with the smallest cost function is removed from the "OPENED" list and inserted into the "CLOSED" list. The node is set as node n (break ties arbitrarily, if two or more nodes have the same cost function). If one of the nodes is in the destination node, then the destination node is selected.
3. If n is the destination node, the algorithm is terminated; otherwise, it continues.
4. The cost function for each successor of n that is not on the "CLOSED" list is computed.
5. Each successor not on the "OPENED" list or CLOSED list is associated with the calculated cost and put on the "OPENED" list.
6. Any successor already on the "OPENED" list is associated with the minimum cost (min(new(f (n)), old(f (n)))).
7. Return to step 2.

V. RESULTS

Initially, the fashions in Section 3 had been used to decide the answers for the route-planning problem. For an optimization version, the answers may be decided through the use of a mathematical solver consisting of CPLEX; for a heuristic approach primarily based totally on the A- star algorithm, the solution is generated through an set up executable module. This calls for excessive-overall performance hardware with excessive computational capacity, wherein the computational runtime varies in step with the size of the enter facts instance. In order to make use of expertise received from formerly solved facts instances, the enter facts instances, in addition to the generated routes, had been gathered and used to construct an ANN version that can pick out a gold standard path. This system calls for the much less computational attempt and is appropriate to put in force on a cell robotic with restricted computing capability. Having to execute a heuristic set of rules or a mathematical solver whenever generating a path is inefficient. This is because, as soon as an ANN is trained, it is able to generate a path with minimum computational attempt and runtime (much less than a second). An ANN education system calls for a server prepared with MATLAB, and it is able to be accomplished each week or while the ANN desires an update.
The shape of a feed-forward ANN version for a route-planning problem is proven in Figure 2. The inputs and outputs of the ANN have been described primarily based totally on a format of the simulated transportation area, which became described via way of means of a two-dimensional grid map. An instance of a grid map is proven in Figure 3.

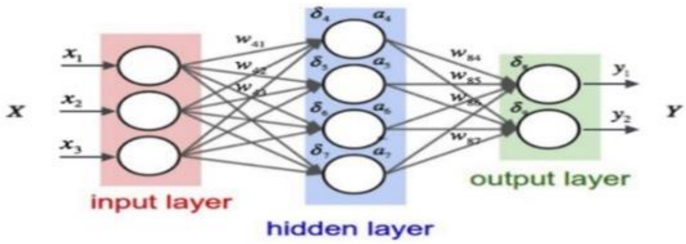

Figure 2. A feed-forward ANN with a hidden layer.

The size of the problem is described with the aid of using the range of rows and columns, which is then used to outline a transportation location, represented with the aid of using a rectangle. In Figure 3, an origin is represented with the aid of using a purple square, and a destination is represented with the aid of using a mild green square. There are varieties of limitations taken into consideration withinside the route-making plans hassle. Fixed limitations (or constant blocks) are represented with the aid of using blue rectangles, and dynamic limitations are inexperienced squares. The range of dynamic limitations may be specified, and they may be generated at random places withinside the transportation location. When the scale of the transportation location will increase, the complexity of the hassle will increase significantly, which calls for impractical runtimes to decide a solution. For instance, there are 3 dynamic hurdles in Figure 3. The decision on direction is represented with the aid of using a red (thick) line, which connects the start line and the destination. The shortest direction may be generated primarily based totally on a shortest-direction version or an A-star algorithm to keep away from collision with all limitations (constant and dynamic) at the grid map. To dispose of beside the point statistics from consideration, a statistics-encoding method is applied. A transportation location with 21 rows × 21 columns is utilized in Figure four to demonstrate the encoding scheme.

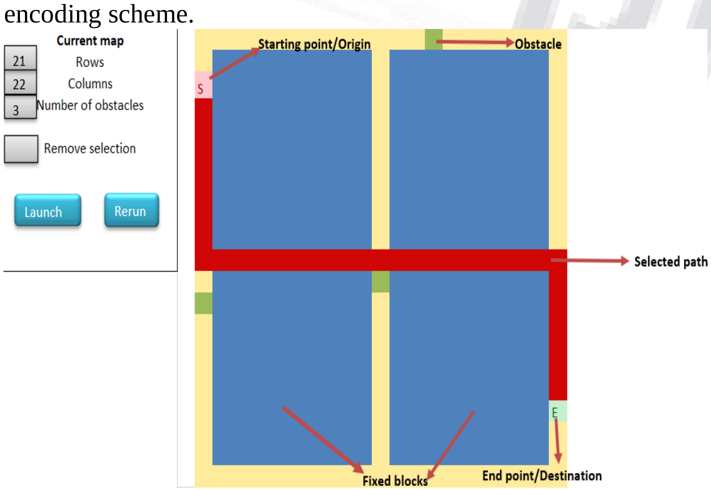

Figure 3. A grid map used for route planning.

To distinguish the different components of the transport zone, each cell is coded according to the following logic: a cell is coded with “1” if it represents a starting point, a destination, or an obstacle; and encoded with “0” otherwise. Note that fixed obstacles are permanent and can be omitted from the model. Because a dynamic obstacle lying on a line intercept blocks the entire segment, an improved coding scheme is proposed to remove noise from the input data. All cells in a blocked segment are encoded with "1". Each segment is named as shown in Figure 5. This encoding scheme reduces the aggregation of input data and greatly reduces the amount of computation required. The output of the ANN is the selected route, consisting of a series of cells from origin to destination. The selected route is encoded with a number (e.g. 0, 1, 2) used to represent the path identifier (ID).

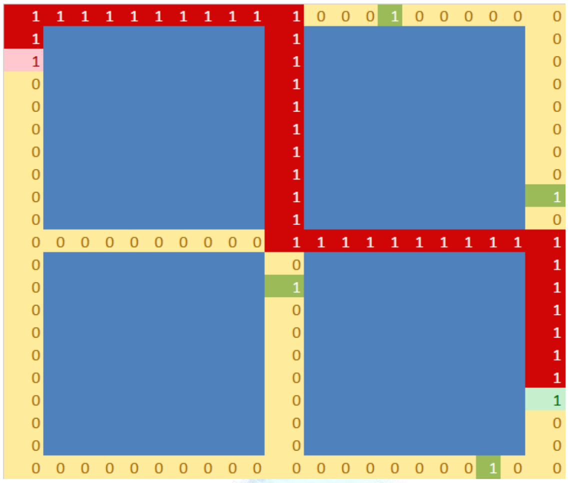

Figure 4. A grid map with encoded data.

In Figures 4 and 5, the selected line is represented by a red (thick) line connecting the origin to the destination. The path is created using the A-star algorithm to avoid collisions with three obstacles that exist on the ×3, ×13 and ×14 segments. However, the obstacles are in the segments in the top right corner. or bottom left corner. Two whole segments at the corner are intercepted at the same time, such as ×3, ×4 and ×7 and ×13, ×16 and ×11. Thus, we can group them into one segment, as in Figure 5b. An example of an input dataset is shown as sample 1 in Figure 6, where the selected path was encoded as type 4.

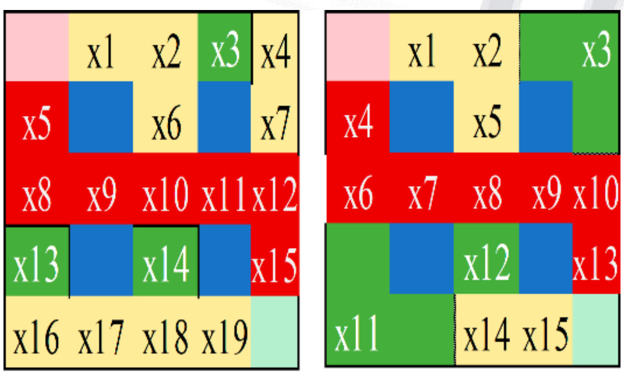

Figure 5. A grid map with an improved encoding scheme: (a) the original encoded map; (b) the map after combining corner segments.

VI. DYNAMIC ROUTE-PLANNING SYSTEM AND COMPUTATIONAL RESULTS WITH MANAGERIAL INSIGHTS

In this section, details of the dynamic routing system are provided and the calculation results of the proposed methodologies for dynamic route planning are provided.

A. DYNAMIC ROUTE-PLANNING SYSTEM

The routes for movement within a DC are initially determined by the shortest path model and an A-star algorithm. If the solutions from the A-star algorithm have high accuracy when compared with the solutions from the shortest path model, the A-star algorithm is used due to the shorter runtime and the computing resources required by the automated guided vehicle. Note that an automated guided vehicle is allowed to carry one shipment at a time, due to the standard size of the pallet that can be loaded into cargo. The input data, which include real-time positions of obstacles, as well as the generated routes, are collected as a training dataset. Once there are enough education datasets, an ANN version for dynamic routing trouble is created and used to decide the routing solution. The quality of the solutions of the ANN model must be checked frequently with the solutions of the shortest path model. A request is specified based on the accuracy of the ANN model; if the accuracy drops below 95%, the ANN model must be updated.

Note that for any internal movement in DC, the gap between the passages narrows; therefore, overcoming obstacles is not possible. If the path segment contains obstacles, it will be excluded from the review. In addition, to account for real-time obstacles during planning, a route is created using the logic provided in Figure 9. At the starting point, a route is created and used. Used to guide vehicle movement. When a vehicle is automatically guided to an intersection, the locations of obstacles are retrieved. Whether the locations are unchanged or not on the generated path, the route does not need to be updated; otherwise, the route must be recreated.

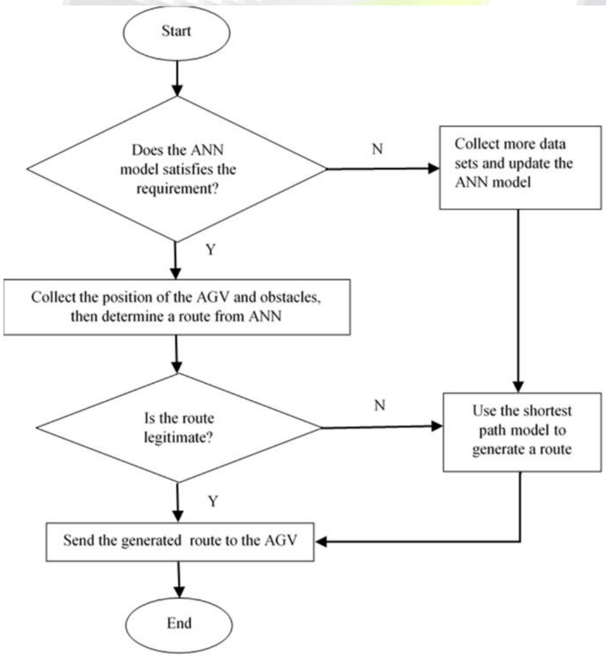

Figure 9. The logic for generating a dynamic route.

B. COMPUTATIONAL RESULTS AND MANAGERIAL INSIGHT

In this section, the calculation results based on the internal warehouse environment with different scales are presented.

1): COMPUTATIONAL RESULTS FROM A LAYOUT WITH FOUR STORAGE RACKS AND 15 SEGMENTS

The layout of the internal DC environment described in Section 5 was used as the transport region to implement the ANN model. Initially, an example configuration consisting of four storage racks with 15 segments was used to test the performance of the proposed method. The definition of all the path segments is shown in Figure 10. Note that the path segments at each corner have been combined. The test data is encrypted and solved using the A-star algorithm and the shortest path model. The results from both approaches were the same in all cases, which shows that the performance of the A-star algorithm is acceptable. There were 13 types of paths generated in the solutions, as shown in Figure 11. Each type was assigned an ID; note that "no way" represents a case where a path between the origin and the destination could not be found.

IJIRMET ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
Vol. 7, Issue 3, March 2022

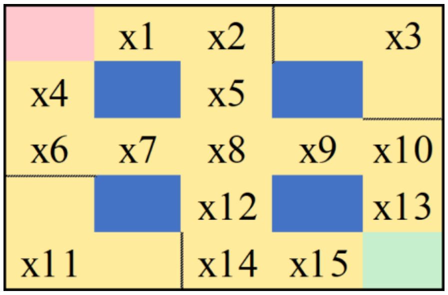

Figure 10. The layout of an internal distribution center (DC) with 15 path segments.
Table 1. Number of cases for each path type. ID, identifier

ID	0	1	2	3	4	5	6	Others
Count	91	32	61	28	67	40	49	7

From Table 1, it could be visible that the simplest seven kinds of paths had been significant; the rest may be taken into consideration as outliers and had been eliminated from consideration. The 375 samples had been separated into 80% education and 20% trying out datasets. An instance of encoded enter statistics is proven in Figure 12, in which x1 to x15 constitute the route segments that have obstacles, and y represents the chosen route ID. The shape of the ANN, that's described through the wide variety of nodes in hidden layers, additionally impacts the accuracy of the ANN model. There are 3 regulations of thumb for figuring out the wide variety of nodes. The wide variety of hidden nodes need to lie among the wide variety of enter functions and the wide variety of goal layers, need to be the same as the sum of -thirds of the enter functions and the scale of the output layer or need to be much less than two times the wide variety of enter feature. featured. The wide variety of hidden nodes in every check needs to range through 3 units.
The number of samples for training should be more than 10 times the number of ANN weights [25], which are defined by the equation, numweights = (i +o) × h [26], where i represents the number of input nodes, o is the number of output nodes, and h is the number of nodes in hidden layers.

IJIRMET ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
Vol. 7, Issue 3, March 2022

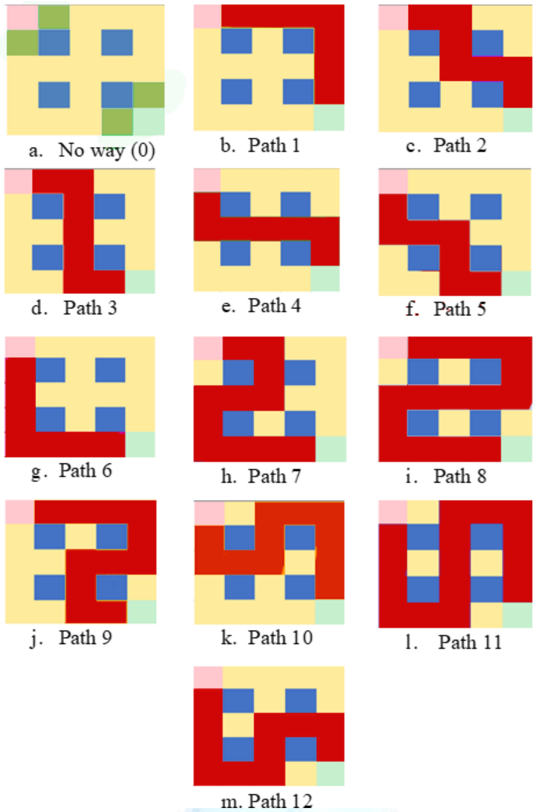

Figure 11. Types of generated paths.

In this study, the learning phase was limited to 1000 iterations. Performance is measured using square root squared error (MSE), where the objective is set to 0. The learning function for the input layer of the ANN is based on the "logsig" function, while, for the first layer Turns out, it's based on a "pureline" function. A network learning function based on a "trainbr" function was used for other classes. Training time is limited to 2 hours. The remaining parameters are set according to the "default parameters" of the MATLAB Neural Network toolkit. The percentages of the accuracy of the training and test phases, using different datasets (with 200 or 300 samples), are summarized in Table 2. Results obtained after the training phase reach 1000 epochs. In Table 2, the percentage of training accuracy varies depending on the ANN structure configuration (number of nodes and layers) and the number of training samples. When increasing the number from samples to more than 300 samples, the ANN model requires a longer training time; however, the accuracy of the model is not significantly improved. Therefore, 300 samples were used to construct ANN.

200 Samples		300 Samples		
ANN's Hidden Layer Topology	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Training Accuracy (%)**	**Testing Accuracy (%)**
15-5-7	93.3	70	92.5	85
15-8-7	100	85	100	96.7
15-10-7	100	75	100	91.7
15-8-7-7	100	95	100	98.3
15-8-10-7	100	90	100	93.3

Table 2. The effect of the number of training samples and ANN configuration on the testing accuracy for a sample layout with 15 segments.

Increasing the number of nodes can help improve the accuracy; however, using too many nodes can cause an overfitting issue. This can be seen when comparing configurations (15-8-7) and (15-10-7). Both configurations contained one input layer with 15 nodes, one hidden layer with eight (configuration (15-8-7)) or 10 (configuration (15-10-7)) nodes, and seven nodes in the output layer. Although configuration (15-10-7) had more nodes, its testing accuracy was 91.7% as opposed to 96.7% (the testing accuracy of configuration (15-8-7)). Moreover, as shown in Table 3, by increasing the number of training data samples from 200 to 300, the accuracy of the configuration (15-8-7) was improved from 85% to 96.7% and that of the configuration (15-10-7) was improved from 75% to 91.7%. Hence, more training samples used resulted in better testing accuracy. The best configuration (15-8-7-7), with a testing accuracy percentage of 98.3%, was used to predict future robot paths for a layout consisting of four storage racks with 15 segments.

2): COMPUTATIONAL RESULTS FROM A LAYOUT WITH 18 STORAGE RACKS AND 67 SEGMENTS

Then, using data collected from the distribution center (DC), an internal layout with 18 racks was created, as shown in Figure 13. There were 67 path segments after combining segments in the corners. From observing actual operations in DC, the number of vehicles (common elevators) working in DC ranges from one to five, with an average of four. Samples with four obstacles had the highest percentage (39%), while the percentage of samples with two, three, or five obstacles was 19%. The lowest rate is 3% for samples with obstacles.

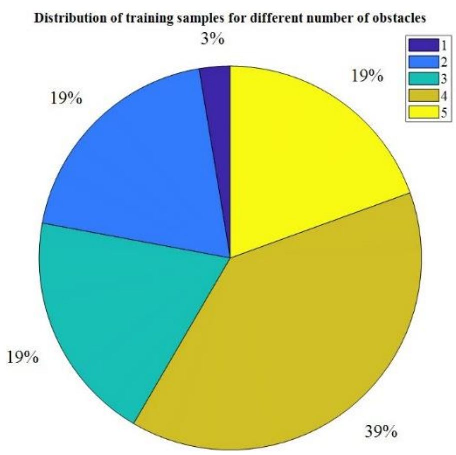

Figure 13. Distribution of training samples for different numbers of obstacles.

Table 3 summarizes the impact of the wide variety of education samples and ANN configuration at the checking out accuracy while a format from a retail warehouse changed into used. There have been 67 variables inside the enter layer, similar to 67 segments of the format, and 21 nodes, which represented 21 forms of paths generated with the aid of using the output layer. The wide variety of hidden

layers and the wide variety of nodes in every layer have been numerous to reap the configuration with nice accuracy. The education accuracy reached extra than 90% for all instances, however, the checking out chances have been distinct among ANN configurations as a characteristic of the wide variety of samples used for education the ANN. As proven in Table 4, on common, the education accuracy chances for instances with 1448 and one thousand samples have been on the identical stage for all ANN configurations. However, the common checking out accuracy for the case with 1448 samples (95.48%) changed into better than that for the 1000 sample case (94.72%).

	1000		1448	
	Training	Testing	Training	Testing
67-60-21	99.7	94.00	99.7	94.83
67-67-21	99.7	93.50	99.7	95.52
67-70-21	99.7	96.00	99.7	96.90
67-73-21	99.7	93.50	99.7	93.79
67-67-21-21	99.7	95.50	99.7	97.93
67-67-30-21	99.7	96.00	99.7	97.24
67-70-30-21	99.7	96.50	99.7	97.93
67-70-40-21	99.25	96.00	99.65	96.55
67-67-21-10-21	90.00	91.50	91.19	88.62

Table 3. The effect of the number of training samples and ANN configuration on the testing accuracy for an actual layout.

In addition to the range of samples, the ANN configuration, described via way of means of the range of hidden layers and nodes, additionally influences the accuracy. Using an insufficient range of nodes within the effects of the hidden layer is an underfitting issue. Underfitting takes place whilst an ANN isn't capable of assembling an ok configuration from a dataset. By supplying enough range of nodes in every hidden layer, the accuracy percent may be improved. Hence, as proven in Table 4, the accuracy of an ANN with configuration (67-67-21) changed better than the share of an ANN with configuration (67-60-21). Similarly, the accuracy percent of an ANN with configuration (67-67-21-21), which changed into the ANN configuration with hidden layers that had the very best accuracy percent (97.93%), changed into better than the accuracy percent of an ANN with configuration (67-70-21), which changed into the quality ANN configuration (96.90%) with one hidden layer.

However, having too many nodes inside the hidden layers can purpose an overfitting issue, wherein an ANN isn't always capable of generalizing the version to pick out output for brand new enter data. Hence, the trying-out accuracy deteriorates. For example, while the number of nodes inside the hidden layer of an ANN configuration (67-70-21) became elevated from 70 to 73 (ANN configuration (67-73-21)), the trying-out accuracy dropped from 96.79% to 93.79%. Similarly, while thinking about ANNs with hidden layers, trying out the accuracy of an ANN with configuration (67-67-21-21) (97.93%) became higher than trying out the accuracy of ANNs with configurations (67-67-30-21) (97.24%) and (67-70-40-21) (96.55%). The maximum trying-out accuracy for instances with one thousand and 1448 samples became 96.5% and 97.93%, respectively, generated with the aid of using an ANN with configuration (67-70-30-21). Both instances had greater than 95% accuracy, that's a criterion for the use of the ANN version cited in Section 6.1. However, the effects for the case with 1448 samples have been greater robust; as a result, the ANN configuration (67-70-30-21) with 1448 education samples became applied withinside the dynamic routing system.

VII. CONCLUSION

In this research, the point of interest became on making use of Industry 4.0 technology, associated with massive statistics analytics, to route-planning of automatic navigation inside a warehouse. Route-planning methodologies for a dynamic routing hassle with the attention of real-time limitations are proposed. An optimization version and a heuristic technique primarily based totally on an A-star algorithm have been used to generate the routes. Machine gaining knowledge of fashions the use of an ANN has been evolved primarily based totally on generated datasets the use of the inner format of a distribution warehouse. Simulation surroundings the use of Gazebo became evolved and used for trying out the implementation of the route-making plans machine. Computational outcomes confirmed that the proposed gadget gaining knowledge of methodologies have been capable of generating routes with trying out accuracy as much as 98% for a sensible inner format of a warehouse with 18 garage racks and sixty-seven direction segments. Managerial insights into how the gadget gaining knowledge of configuration may be decided on have been additionally provided. The route-making plans machine may be used to generate routes for extraordinary varieties of AGVs in real-time. This is useful to the transportation enterprise considering there can be an immediate discount in hard work price and a boom in operational efficiency, which is critical to be aggressive in today's enterprise surroundings. The trouble of our proposed method is primarily based totally on the specified education datasets for the ANN. If the datasets want to be amassed from a real operation, this could require an extended statistics series period. However, simulated datasets also can be used, which could assist boost up the ANN education process.

A viable destiny studies place consists of the attention of different routing issues consisting of the car routing problem. In this study, every AGV becomes assumed to make one prevent in line with the inner motion inside a warehouse. However, in a regular car routing problem, a vehicle has a bigger capability and might make more than one stop. This calls for the attention of needs and car capability in an ANN education process, wherein appropriate information encoding for entering and output datasets want to be determined.

REFERENCES

[1] Palka, D.; Ciukaj, J. Prospects for development movement in the industry concept 4.0. Multidiscip. Asp. Prod. Eng. 2019, 2, 315–326. [CrossRef]
[2] AI and Robotics Automation in Consumer—Driven Supply Chains: A Rapidly Evolving Source of Competitive Advantage. PA Consulting Group and the Consumer Goods Forum. 2018. Available online: https://www.theconsumergoodsforum.com/wp-content/uploads/2018/04/201805-CGF-AI-Robotics- Report-with-PA-Consulting.pdf (accessed on 1 June 2018).
[3] D'Andrea, R.; Wurman, P. Future challenges of coordinating hundreds of autonomous vehicles in distribution facilities. In Proceedings of the 2008 IEEE International Conference on Technologies for Practical Robot Applications, Woburn, MA, USA, 10–11 November 2008; pp. 80–83.
[4] Liu, X.; Gong, D. A comparative study of A-star algorithms for search and rescue in the perfect maze. In Proceedings of the 2011 International Conference on Electric Information and Control Engineering, Wuhan, China, 25–27 March 2011; pp. 24–27.
[5] ElHalawany, B.M.; Abdel-Kader, H.M.; TagEldeen, A.; Elsayed, A.E.; Nossair, Z.B. Modified a* algorithm for safer mobile robot navigation. In Proceedings of the 2013 5th International Conference on Modelling, Identification and Control (ICMIC), Tianjin, China, 13–15 July 2019; pp. 74–78.
[6] Contreras-González, A.-F.; Hernández-Vega, J.-I.; Hernández-Santos, C.; Palomares-Gorham, D.-G. A method to verify a path planning by a back-propagation articial neural network. In Proceedings of the LANMR, Puebla, Mexico, 15 August 2016; pp. 98–105.
[7] Zhang, Y.; Li, L.-l.; Lin, H.-C.; Ma, Z.; Zhao, J. Development of Path Planning Approach Based on Improved A-star Algorithm in AGV System. In proceedings of the International Conference on Internet of Things as a Service, Taichung, Taiwan, 20–22 September 2017; pp. 276–279.
[8] Gochev, I.; Nadzinski, G.; Stankovski, M. Path Planning and Collision Avoidance Regime for a Multi-Agent System in Industrial Robotics. Mach. Technol. Mater. 2017, 11, 519–522.
[9] Mohan, L.J.; Ignatious, J. Navigation of Mobile Robot in a Warehouse Environment. In Proceedings of the 2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR), Arakkunnam, India, 11–13 July 2018; pp. 1–5.
[10] Kurdi, M.M.; Dadykin, A.K.; Elzein, I.; Ahmad, I.S. Proposed system of artificial Neural Network for positioning and navigation of UAV-UGV. In Proceedings of the 2018 Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT), Istanbul, Turkey, 18–19 April 2018; pp. 1–6.
[11] Zhang, Y.; Zhang, Y.; Liu, Z.; Yu, Z.; Qu, Y. Line-of-Sight Path Following Control on UAV with Sideslip Estimation and Compensation. In Proceedings of the 2018 37th Chinese Control Conference (CCC), Wuhan, China, 25–27 July 2018; pp. 4711–4716.
[12] Flórez, C.A.C.; Rosário, J.M.; Amaya, D. Control structure for a car-like robot using artificial neural networks and genetic algorithms. Neural Comput. Appl. 2018, 32, 1–14.
[13] Zhong, X.; Tian, J.; Hu, H.; Peng, X. Hybrid Path Planning Based on Safe A* Algorithm and Adaptive Window Approach for Mobile Robot in Large-Scale Dynamic Environment. J. Intell. Robot. Syst. 2020, 99, 1–13. [CrossRef]
[14] Bhadoria, A.; Singh, R.K. Optimized angular a star algorithm for global path search based on neighbor node evaluation. Int. J. Intell. Syst. Appl. 2014, 6, 46. [CrossRef]
[15] Zhang, Z.; Zhao, Z. A multiple mobile robots path planning algorithm based on A-star and Dijkstra algorithm.
Int. J. Smart Home 2014, 8, 75–86. [CrossRef]
[16] Kusuma, M.; Machbub, C. Humanoid robot path planning and rerouting using A-Star search algorithm. In Proceedings of the 2019 IEEE International Conference on Signals and Systems (ICSigSys), Bandung, Indonesia, 16–18 July 2019; pp. 110–115.
[17] Ruiz, E.; Soto-Mendoza, V.; Barbosa, A.E.R.; Reyes, R. Solving the open vehicle routing problem with capacity and distance constraints with a biased random key genetic algorithm. Comput. Ind. Eng. 2019, 133, 207–219. [CrossRef]
[18] Salavati-Khoshghalb, M.; Gendreau, M.; Jabali, O.; Rei, W. An exact algorithm to solve the vehicle routing problem with stochastic demands under an optimal restocking policy. Eur. J. Oper. Res. 2019, 273, 175–189. [CrossRef]
[19] Zhang, H.; Zhang, Q.; Ma, L.; Zhang, Z.; Liu, Y. A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. Inf. Sci. 2019, 490, 166–190. [CrossRef]
[20] Sung, I.; Choi, B.; Nielsen, P. On the training of a neural network for online path planning with offline path planning algorithms. Int. J. Inf. Manag. 2020. [CrossRef]
[21] Pasha, J.; Dulebenets, M.A.; Kavoosi, M.; Abioye, O.F.; Wang, H.; Guo, W. An Optimization Model and Solution Algorithms

for the Vehicle Routing Problem With a “Factory-in-a-Box”. IEEE Access 2020, 8, 134743–134763. [CrossRef]
[22] Trachanatzi, D.; Rigakis, M.; Marinaki, M.; Marinakis, Y. A Firefly Algorithm for the Environmental Prize-Collecting Vehicle Routing Problem. Swarm Evol. Comput. 2020, 57, 100712. [CrossRef]

[23] Taccari, L. Integer programming formulations for the elementary shortest path problem. Eur. J. Oper. Res. 2016, 252, 122–130. [CrossRef]
[24] Klancar, G.; Zdesar, A.; Blazic, S.; Skrjanc, I. Wheeled Mobile Robotics: From Fundamentals towards Autonomous Systems; Butterworth-Heinemann: Oxford, UK, 2017.
[25] Baptista, F.D.; Rodrigues, S.; Morgado-Dias, F. Performance comparison of ANN training algorithms for classification. In Proceedings of the 2013 IEEE 8th International Symposium on Intelligent Signal Processing, Funchal, Portugal, 16–18 September 2013; pp. 115–120.
[26] Panchal, G.; Ganatra, A.; Kosta, Y.; Panchal, D. Behaviour analysis of multilayer perceptrons with multiple hidden neurons and hidden layers. Int. J. Comput. Theory Eng. 2011, 3, 332–337. [CrossRef]

IJIRMET