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A Comprehensive Survey on Deliveries by Unmanned Vehicle using AI

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***Abstract*—In the course of the demi-decade, there has been tremendous and significant growth in the field of scientific research based on Artificial Intelligence Capable Autonomous Unmanned Aerial Vehicle (UAV) i.e. drones. Implementing artificial intelligence for drones is a combination of mechanical devices, navigational instruments, and machine vision. The major challenge today is the advancement of autonomously operating aerial vehicles that are capable of completing given tasks without human intervention. The motive/aim of this article is to provide an exhaustive overview of vision-based applications mainly focusing on UAV-based delivery systems. This application can be categorized into several domains that include the physical design of UAVs so as to be customized for delivery systems, path-planning, real-time target tracking, navigation using Machine learning and Computer Vision, pedestrian detection, and their algorithms. Furthermore, a unique combination of truck-drone and train-drone delivery methodologies will be discussed briefly.**

***Index Terms*—UAV, Artificial Intelligence, Drone delivery system, Navigation.**

I. INTRODUCTION

With the popularity of E-commerce websites, package delivery has become an integral part of the logistics business. Conventionally, package delivery is carried out through land transportation such as trucks, trains, and motorcycles that are inexpensive, reasonable, and economically viable. The desideratum for an alternative to these is necessary due to an increase in labor costs and a sharp rise in traffic congestion, particularly in metropolitan cities. The use of autonomous Unmanned Aerial Vehicles also known as UAVs is catching everyone's attention [1][2]. With the advancement of drone technologies, the cost and reliability of drones in the application of package and medical delivery [3][4] have been ameliorated significantly.

With the advent of Fortune companies adopting drone delivery services such as Amazon Prime Air [5], Google Project Wing, DHL Parcelcopter, and other major companies conveying the technological and economic feasibility of the services.

Apart from major companies, several startups have also been working on UAV delivery systems, as a purpose for last-mile connectivity. Matternet founded in 2011 which is famous for its specialization in developing lightweight drones has raised a whooping 34M USD for enhancing autonomous delivery solutions. Volans-I startup founded in 2015 has been funded with USD 20M for developing UAV for logistics applications which majorly includes delivering spare parts and medical supplies.

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Elroy Air founded in 2016, located in San Francisco (United States), is a UAV startup that has been funded USD 21M for designing and developing UAVs for delivering goods to remote places. The startup primarily focuses on supplying commercial cargo and military applications. Manna, an online food delivery platform located in Dublin (Ireland), the startup is bankrolled by major companies with an estimated amount of USD 18M for delivering food with the help of drones. Dash Systems, a cargo delivery service startup located at Chatsworth (US) has been bankrolled with USD 4M for developing drones that can deliver up to 20 kilograms of food, medicine, and other essentials. Figure [1] depicts the amount funded by major companies in top startups to enhance and develop drones specialized for delivery purposes.

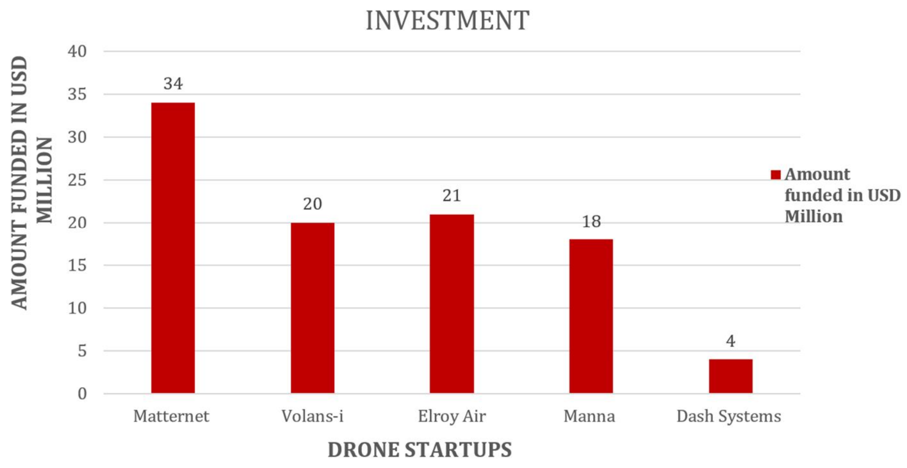

Fig 1. UAV Funded Startups

One of the pros of the drone delivery system is its duration of package delivery when compared to traditional or conventional methodologies. Since every step involved in the delivery method is completely automated, it is bound to have less service time as the drones can drop the package directly to the customers with less or no human intervention involved [6]. Above all, drone delivery is quite feasible in areas of rough terrain that are difficult to access by land transportation. Thanks to the recent advancements in the field of Machine learning and Conventional Neural Networks enabled autonomous drones to locate the destinations and detect the obstacles efficiently leading to establishing accurate last-mile connectivity to the customers. With the help of data analytics and data acquisition, the UAV's potential can be enhanced.

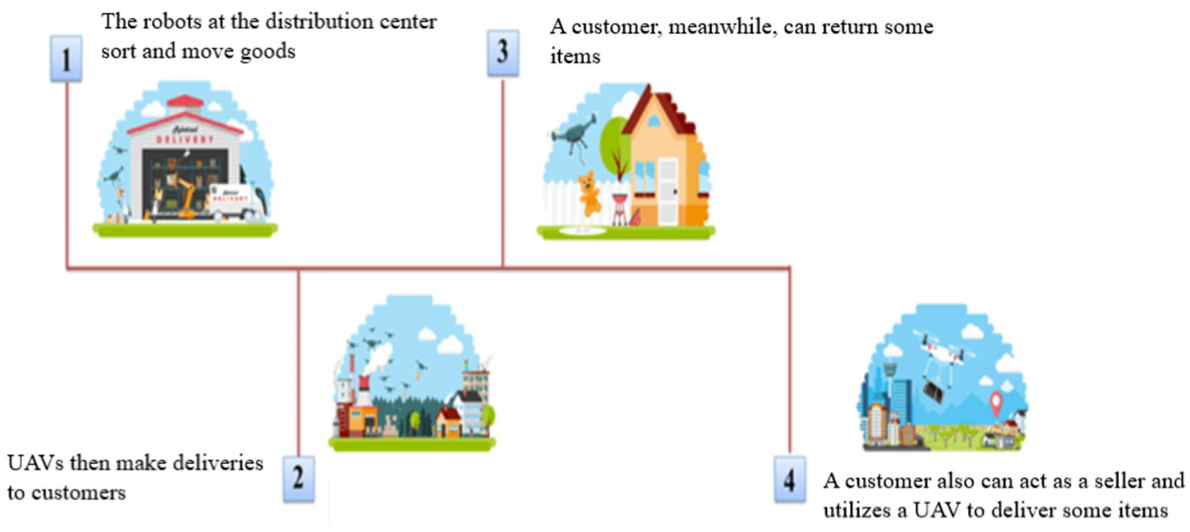

Fig 2 Autonomous E-commerce

To enhance the drone's independent flight control, an enormous amount of data is required. Sensor technologies have evolved over the years and are considered as the secret ingredient for the drones that help in remote sensing applications. Furthermore, these sensors help the drone by enhancing its self-awareness of its surroundings and the context it is flying to take reactive actions. Moving on from the pros of the drone, let's move forward to the challenges faced.

In comparison to the ground-delivery system, drone delivery is less reliable as drones are subjected to less coverage area and capacity [7]. It is not appreciable to use only drones for package delivery as they may lack a huge battery backup to deliver the package over long distances thereby significantly reducing the payload to be carried.

Fig 2 Illustrates a novel approach to the delivery or transport of food, packages, and other goods using Unmanned Aerial Vehicles.

The Authors in [8][9] have reported a detailed description of delivery applications about the locations where drones can be deployed and how Artificial Intelligence is being collaborated with existing drones to ease the delivery prospects ranging from Merchandise delivery to Humanitarian aid. The author in [8] has even provided the necessary regulations and how they may affect the drone-based delivery systems and the risks involved. The paper will speak about the violation of privacy issues involved and details on eliminating the economic viability of technology. Furthermore, the author has provided a detailed analysis of drone capability for commercial delivery purposes.

The article is summarized as follows:

Section 2 gives a detailed description of the physical design of autonomous drones customized particularly for delivery-based applications. Section 3 provides an in-depth view of various algorithms used for navigational purposes. Section 4 discusses various obstacles and human detection methods using Machine Learning and Computer Vision. Section 5 provides an overview of delivery schemes.

II. PHYSICAL DESIGN

For the delivery or transportation of goods, the physical design of the drone must be accurately manufactured to support the payload accordingly [10][11]. Drones can also be classified based on the weight involved in a particular package. In the article, the author briefs various physical parameters required to construct the drone and withstand the payload delivery of 500 grams for a particular range.[18]Specifically describes each parameter such as Motors and Propellers, Electronic Speed Controller, Transmitter and Receiver, Camera for high resolution, Battery, and frame size. A detailed estimation of the total weight of a UAV system has been provided in Table [1] below. The design calculations based on the payload requirement are mentioned in the article. One of the advantages includes it being helpful in crowd monitoring and reduction in the time of delivering the load. The drawback of the proposed system is the experimented payload aspect; the drone can carry only 250g of payload and ultimately lacks accuracy in the design prospects

TABLE I. WEIGHT ESTIMATION OF UAV SYSTEM

Part Description	**Average Weight (gms)**	**Quantity**	**Final Average Weights(gms)**
Flight Controller	80	1	80
Propellers	7	4	28
Receiver	13	1	13
Motors	50	4	200
ESC	20	4	80
Battery	150	1	150
Frame	270	1	270
Payload	500	1	500
Camera	4.5	1	4.5
Miscellaneous	100	1	100

Mr. Md. R Haque, in his article [13] has appreciably described a typical parcel delivery using a UAV, right from placing an online order to payload calculations to be carried by the drone. The paper provides an overview of an ideal onboard control system that is interfaced with Android [13][14] and Google Maps to establish proper communication and regular updates. The author in [13] has well described the payload calculations with suitable formulae in consideration of the battery and onboard sensors involved. Along with these, the author has provided flight test results with various payloads and their respective flight durations. The paper can well be commercialized only for a lightweight payload with an estimation of 300 grams. One of the drawbacks of the article is the flight duration. On analyzing the test results, for a payload of 300g, the flight duration is only a mere 13 minutes. This is mainly due to the limited amount of power supply from Lithium polymer batteries. It lacks a mutual relationship between the power supply and payload weight. Above all the article also suggests solutions to overcome the power-related issues which can optimize the cost of delivering products.

It is not feasible for a single drone to transport goods of all weights. Moreover, the drones are to deliver one particular package at a time. Hence, it is necessary to research alternate options to optimize delivery systems. Thanks to Mr. Hanlin, who, in his article [15], who has suggested a weight-based scheduling scheme, which considers the priority and delivery distance of service requests. The paper remarkably explains a UAV-based system with multiple regions and a head control center that manages and receives service requests to deploy UAVs assigned to their respective regions. Resulting in increasing the probability of successfully managing the service requests from a system aspect. The paper magnificently briefs up on the weight–scheduling scheme and how it overcomes hurdles involved in drone delivery systems.

Moreover, it proposes an optimal UAV allocation scheme that maximizes the probability that the arriving requests can be handled. The article also provides brief experimental data of the above idea and suggests a Demand Node Generation Algorithm to design and deploy regions for supporting UAV delivery. Above all, the author has well-documented the analysis of the results obtained during the observations. Though the ideal calculations get synchronized with the optimization of UAV delivery, it lacks the real-world operation of the UAV delivery based on the "Weight-based" scheduling scheme as well as the robustness and security involved during package delivery.

III. UAV PATH PLANNING AND NAVIGATION

For an efficient UAV delivery, it is important to navigate the UAV autonomously in the right direction or the shortest route possible to utilize time and consume the right amount of power supply to complete the delivery. Here, we discuss various algorithms used in path planning and navigation systems.

In the previous section, major drawbacks were mostly based on flight time duration due to battery constraints. In this paper [16], the author has taken an approach to solving the long-duration haul of drones by utilizing the existing public transport system. It presents a stochastic model to characterize the path traversal time and implement a label-setting algorithm to determine a reliable and efficient drone path. This paper approaches a novel methodology utilizing public transport to its full capability for drone parcel delivery systems. It offers valuable insights about the extended model to consider battery life so that the path is not only reliable but economically feasible too. Above all, the proposed algorithm is analyzed with a unique case study. One of the benefits of the literature is that it provides an efficient procedure to eliminate power supply consumption, particularly during the transportation of goods to far-off distances.

The major drawback of the literature is the non-availability of the results and datasets by implementing the proposed algorithms in a commercial drone.

In this article [17], the author has proposed a reliable path-planning algorithm to enable low-delivery drones at the city scale. The proposed planning algorithm utilizes a random tree methodology to maintain a safe distance from other UAVs and geofenced objects. Key insights from the paper are an alternative solution proposed in comparison to existing solutions available that do not consider geofencing aspects. Even after implementing Heuristic-based termination criteria, their conducted experiments remain unsuccessful. Papers [18][19][20] consist of various path planning algorithms used for drone delivery.

The author has provided a broad comparison of various algorithms based on several critical parameters to optimize the shortest path for UAVs. The author in [18] has compared the algorithms based on the threat of fixed obstacles and based on the addition of sudden threats to the working environment of UAVs near the starting point and ending point. The table is given below consisting of run-time and path length details for the four algorithms. The data indicate that all four algorithms can handle fixed and sudden threats. Above all, their planning times are short. However with in-depth analysis, the simulation shows that the Dijkstra algorithm is better than the previous algorithms.

TABLE II. PATH PLANNING TIME OF FOUR ALGORITHMS

Algorithm	Number of experiments	Average run time for three situations(s)	Average run time for three situations(s)
Dijkstra	25	3.029996	1.01
Floyd	25	3.06997	1.0233
Ant	25	3.383045	1.1277
A*	25	3.278161	1.0927

TABLE III. 3D PATH LENGTH OF FOUR ALGORITHMS UNDER THREE OBSTACLE CONDITIONS

Algorithm	Three fixed terrain obstacles condition	With a sudden threat near the starting point	With a sudden threat near the target point
Dijkstra	1046.6	1046.6	2065.5
Floyd	1046.6	1046.6	2065.5
Ant	3869.1	3869.1	4146.6
A*	4023.5	3878.1	3878.1

For establishing a completely autonomous system, image recognition has been widely used for UAV navigation in recent years, allowing independent navigation based on visual aspects of the environment, independent of a satellite. The literature [21] provides an in-depth analysis of various classifiers for the evaluation of the navigation technique through visual–topological maps. Several extractors were used along with the classifiers to determine the accuracy.

All the classifiers were tested based on 4 metrics viz- Specificity, Sensitivity, positive predictive value and accuracy. The best values cited are shown in the below table for a detailed study purpose.

TABLE IV. CITED VALUES

Feature	Classifier	Specificity (%)	Sensitivity (%)	Positive Predictive Value (%)	Accuracy (%)
Fourier	Bayes (Normal)	99.951± 0.024	91.802± 0.471	92.589± 0.373	99.223± 0.045
	kNN	99.718± 0.021	94.155± 0.415	94.122± 0.427	99.438± 0.039
	MLP	97.122± 0.761	42.392± 15.202	42.172± 16.209	94.512± 1.447
	OPF(Euclidean)	99.806± 0.028	95.993± 0.554	95.976± 0.566	99.617± 0.053
	SVM(Linear)	99.611± 0.024	92.226± 0.475	92.167± 0.491	99.259± 0.045
GLCM	Bayes (Normal)	99.591± 0.009	98.971± 0.192	98.973± 0.191	99.905± 0.018
	kNN	99.839± 0.012	96.500± 0.242	96.502± 0.236	99.672± 0.023
	MLP	97.613± 0.226	52.137± 4.528	51.361± 3.525	95.436± 0.431
	OPF(Euclidean)	99.915± 0.009	98.253± 0.198	98.254± 0.199	99.831± 0.019
	SVM(Linear)	99.918± 0.007	98.249± 0.135	98.241± 0.137	99.835± 0.013
LBP	Bayes (Normal)	99.984± 0.006	99.619± 0.119	99.615± 0.118	99.958± 0.011
	kNN	99.972± 0.006	99.458± 0.115	99.453± 0.115	99.951± 0.011
	MLP	99.983± 0.008	99.532± 0.161	99.538± 0.162	99.964± 0.015
	OPF(Euclidean)	99.987± 0.006	99.699± 0.123	99.694± 0.122	99.969± 0.012
	SVM(Linear)	99.991± 0.005	99.744± 0.069	99.776± 0.069	99.985± 0.007

It is clear that the LBP extractor with an SVM classifier, operating with a linear kernel, obtained the highest percentage for the metrics evaluated.

Though it has achieved greater accuracy and utilized Computer Vision technology as an alternative to the existing GPS sensors, one of the drawbacks of the paper is its inability to process during real-time, which is particularly due to the lack of embedded GPUs with low power consumption and use of advanced machine learning techniques and CNN architectures.

These drawbacks have been addressed and a novel solution is provided in the literature [22][23][24]

VI. OBSTACLE DETECTION AND HUMAN DETECTION

Apart from efficient path planning for package delivery, it is crucial to locate obstacles and humans with the highest precision. In recent times, with the help of Machine learning and deep learning,[25][26] UAVs have been able to detect obstacles to some extent with more accuracy as compared to previous existing techniques[27]. This has been well explained by Widodo and Liang in their literature by MobileNet and Single Shot Detector (SSD)[28][29] framework for super-fast and efficient object detection using Deep-Learning methodology. Experiments were conducted using popular deep learning architectures viz GoogleLeNet, ResNet, and VGGNet. Through the conducted experiments [28], it is observed that the combined MobileNet and SSD framework provide more accuracy [72.2% mAP (mean average precision)] and a faster processing speed of the camera as compared to a faster R-CNN algorithm. Accuracy is achieved with the same SSD framework and parrot drone in the literature [30] authored by Ali Rohan. The paper compares all the previous and current CNN-based object detections viz R-CNN, R-FCN, YOLO[31], and SSD. Here the SSD approach is purely based on the feed-forward convolutional network. The readings from the paper have indicated that it is required to use a split-model method that was previously not used in [28] and failed to achieve greater accuracy as compared to [30] which produces a stunning 98% as compared to other CNN algorithms.

The literature proposes a novel approach focused only on small-sized drones. It fails to provide a foolproof solution for larger-sized drones thus being the only disadvantage of the literature. Moreover, the greatest challenge is to implement the novel algorithm on an embedded AI which usually has a large computational time. The advantage is its feasibility of implementing a novel strategy in a complex system like drones. Not only obstacle detection is necessary, but human recognition is also equally important for a proper autonomous delivery system, thanks to Mr. David and Barros who in their literature [32][33] proposed a novel solution for human detection using Computer Vision that allows determining the location of an individual from an aerial perspective for drone-based delivery service to detect the potential customer or receiver with greater accuracy. The below figure represents the architecture of the human detection system.

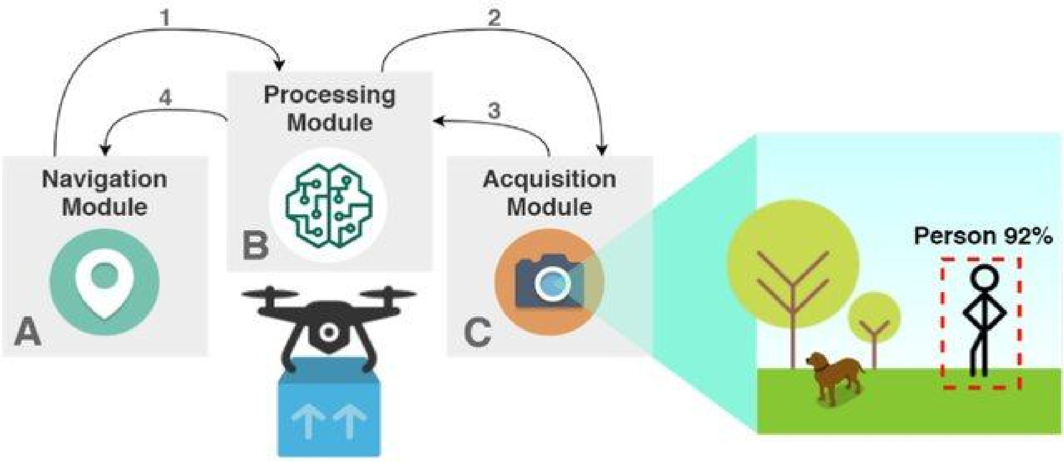

Fig 3 Architecture of Human Detection System

The author uses SSDLite with the feature extractor MobileNet with the help of an existing COCO dataset [34] that is available to use directly on the TensorFlow framework. The author in [32] has implemented the CNN models in a small-powered ARM architecture device. The experiments were conducted for detection purposes by placing the camera at different angles from the people with varying vertical distances. Table 5 represents Horizontal and vertical distances, the CNN model used and several samples as metrics.

It is observed, by placing the camera at a height of 4.5m along with a distance of 5m from the humans, an accuracy of 71% is achieved.

Increasing the height to 10m, a significant drop of 10% accuracy was observed. From the use of 24 samples with a single person, the algorithm could detect the person in 22 samples which represent an accuracy of approximately 92%. The disadvantage is the consideration of a few samples for the CNN model, a large dataset is a primary prerequisite to achieving great accuracy without any issues in recognizing humans. Moreover, the drone is only able to detect humans when the distance is a mere 4.5m to 5m. For a longer distance, the models fail to recognize humans. Above all, a wider diversity of human morphology and poses is required to develop a more accurate model.

TABLE V: COMPILATION OF THE TEST RESULTS WITH TWO INDIVIDUALS

HD (m)	VD (m)	Model	Samples	TP	FP	FN	Avg Conf	Accuracy	Avg Time (s)
5	4,5	SSDLite MN-V2	24	34	0	14	0.7207	0.7083	1.1925
	10	SSDLite MN-V2	67	68	0	42	0.7230	0.6181	1.1811
10	4,5	SSDLite MN-V2	45	32	1	53	0.6800	0.3764	1.1877
	4,5	SSD MN-V2	45	31	3	54	0.6736	0.3647	2.5554
	10	SSDLite MN-V2	40	3	7	82	0.7386	0.0352	1.1835
	10	SSD MN-V2	40	14	12	71	0.6359	0.2000	2.472

V. UAV DELIVERY SCHEMES

Having seen the physical design, path planning, navigation, obstacle, and human detections for an autonomous UAV that makes it 70% of the total package, a proper delivery system should be present to implement all the parameters and algorithms, thus making it a complete package for autonomous delivery. In recent years this system has been evolving for commercial purposes. One of the most important factors to be considered before finalizing the delivery system is the battery management system of drones. Delivery methods should be designed or optimized in such a way that the battery does not drain out during delivery service [35]. A unique combination of UAV and Public Train [36] has been proposed. Here the UAV can travel by train and replace its battery if required. The author has presented algorithms that provide an optimal schedule and a computationally efficient suboptimal algorithm with realistic simulations to evaluate the proposed algorithm. The literature also considers a sole UAV system and truck-based UAV systems [37][38][39] for comparison purposes. The proposed algorithm is based on brute and force search. On observing the results, it was noticeable that the suboptimal algorithm performs better in running time in consideration of the various metrics involved. One of the challenges is the accurate scheduling of drones following public train timetables which should be well-tested before rolling out commercially. Having discussed the proper delivery system, two factors that are of utmost importance to consider are the battery capacity payload and management strategy for delivering goods. Adopting modularity in drone design could prove to be a great benefit and apparently, author Jaihyun in his literature [40] has proposed a near-perfect efficient solution to overcome the pertaining problems. The literature addresses the issues in non-modular systems and does an in-depth comparison between the existing non-modular and novel modular drone delivery systems with the help of simulations. The paper proposes a modular design with swappable batteries which is shown to perform better in comparison to integrated batteries in terms of readiness. An optimization algorithm with a forward-looking approach is designed and compared to existing dynamic programming [40] scenarios. The proposed operation of modular drones is shown below as a reference.

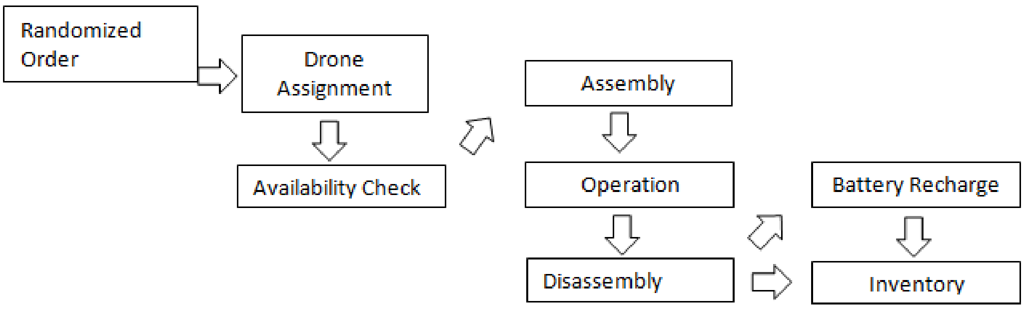

Fig 4 Operation of Modular Drones

The proposed results are far better as compared to previously existing algorithms. Simulations were performed corresponding to three different algorithms briefly discussed in [40]. It appears that the modular drone delivery system has great potential to improve the delivery time in comparison to the existing non-modular system. One small drawback is that the author does not discuss the long-term analysis of both systems which otherwise might be an interesting aspect to look at.

VI. CONCLUSION

Industries are going through a tremendous transformation and the delivery industry is one among them. The drone delivery system is an impactful change in it. The precise design of the drone is a crucial part of carrying the payload over large distances [41]. In recent years, machine learning and deep learning, a subset of Artificial Intelligence have been widely implemented in autonomous drones resulting in a reduction of human involvement. This paper widely discusses various algorithms used for path planning, navigation, obstacle, and human detections and their reliability in the real world. The papers that are discussed are segregated into 4 categories viz. physical design, path planning and navigation, obstacle and human detection, and delivery systems. Each algorithm discussed achieves a competitive performance under different conditions and corresponding metrics involved. From this extensive comprehensive survey, researchers can get to know the complete package right from the design phase to computational algorithms for an enhanced and efficient drone delivery system with less processing time and greater accuracy.

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