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Research Article

Integration Of Artificial Intelligence And Machine Learning In National Food Service Distribution Networks

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ARTICLE INFO **ABSTRACT**

The unprecedented COVID-19 pandemic has revealed a chaotic vulnerability in the distribution of food service. People around the world were prevented from getting food products, which weakened international relations and placed governments on high alert. Meanwhile, in developed countries, an oversupply of food commodities caused serious food-waste problems, while in developing countries, food scarcity became critical. In addition, about 1 million people worldwide are food-insecure and in need of food assistance. How to effectively allocate food for food service is key to reduce excess surplus and perform food distributions. This chapter considers the complex problem of food distribution networks by integrating artificial intelligence and machine learning techniques in the process of demand-supply forecasting, food distribution allocation, and vehicle routing. The demand data from food banks and the supply-inventory data from food suppliers can only be better predicted through effective analytics and algorithms, and the transportation routes can only be better optimized through effective routing intelligence. In the post-Covid-19 era, the new technologies brought by these artificial-intelligent and machine-learning techniques provide the food industry with greater opportunities for enhancements.
Food assistance is essential to society, where a supply surplus cannot solve hunger, but distributions do; however, the transportation of food products from suppliers to food service recipients is complicated, as these services are often provided by multiple food banks and distributors. With the aid of the latest artificial-intelligence and machine-learning algorithms, the food shortage can be addressed and the food waste shortage can be reduced through better demand forecasts and larger allocation efficiencies. To minimize the transportation times and maximize the safety of food recipients, shorter transportation routes are also desirable.

Keywords: COVID-19, Food Distribution, Food Insecurity, Food Surplus, Food Scarcity, Artificial Intelligence, Machine Learning, Demand Forecasting, Supply Allocation, Vehicle Routing, Food Banks, Supply-Inventory Data, Routing Intelligence, Post-Pandemic, Transportation Optimization, Distribution Efficiency, Food Waste Reduction, Demand-Supply Balance, Allocation Algorithms, Food Assistance.

1. Introduction

For various reasons, the physical distribution of perishable food products in the United States is unique in its organization and physical structure. At primary and secondary processing operations, individual product commodity lots are often mixed together to create bulk-size shipments of frozen foods that are sent to multiple warehouses across the country. These warehouses are located in regions where demand for those specific products are greatest. Bulk shipments of perishable food products are usually sent to regional warehouses for storage and are redistributed in truckload, less-than-truckload, and route-deliver-size shipments to food service operators. Distribution to food service and convenience store operators follow planned time schedules, such as every day, every two days, once per week, every other week, and once per month at specific quantities. Mobile technology, product tracking devices, and handheld personal digital devices have been implemented to some extent by some distributors. However, in most situations, the advanced technologies have not been fully integrated into either outbound or inbound logistics operations.

Integration appears intellectual, requiring an examination of the concepts and definitions associated with distribution and supply chain. The definition of food service distribution is the physical transfer and storage of bulk-size quantities of market-destined food products from manufacturer exits to storage facilities located close to the operators who prepare and serve those products to their customers. An integrated supply or distribution chain refers to the unified control of a seamless chain, consisting of a number of players such as a grower, a shipper/processor, secondary wholesalers, distributors, and retail and food service operators. Supply chain strategy refers to decisions which influence the development of long-term capabilities in the fields of logistics, manufacturing marketing, and product development services. Advanced technology has been used to manage food service distribution in the last forty years.

1.1. Introduction to Food Service Distribution and AI Integration

Efficient and effective food service distribution is fundamental to the preparation of meals served to patients in hospitals and residents in nursing facilities. National distribution of food to licensed food service directors and their staff is accomplished by complex networks of integrated resources moving food into, between, and out of stores and distribution centers. As healthcare costs continue to rise at a rate greater than the economy as a whole, and as hospitals and nursing homes struggle for profitability and even solvency, food service directors, their staffs, and commercial food service distributors are charged with reducing costs. With receipt of an order by a distributor, the work of the distributor itself begins. Human action at the distributor may include, but is not limited to, receipt of the order; selection of food and supplies to fill the order; receipt of food and supplies from the supplier; packing of food and supplies to fill the order; loading of food and supplies onto a delivery vehicle; movement of the delivery vehicle to the customer site; unloading of food and supplies from the delivery vehicle; completion of billing and documentation; and return of the delivery vehicle to the distributor location.

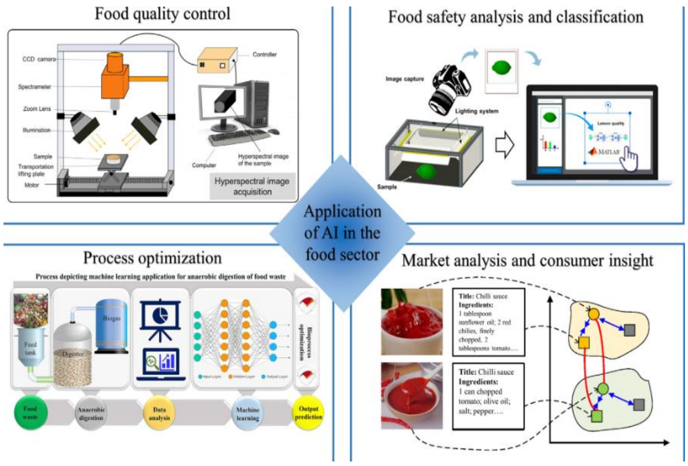

Fig 1: Artificial Intelligence in Food Industry

This chapter describes the application of artificial intelligence and machine learning techniques to the movement of food and supplies between the supplier's supplier, food source, manufacturer, package, processor, distributor, store and stock, delivery vehicle, customer site, and consumer's plate, as well as the return of packaging, distribution, and delivery resources for the purpose of addressing each contact point in the distribution network with regard to cost reduction and profitability optimization in the movement of food to support food service in healthcare venues: nursing homes, assisted living facilities, psychiatric hospitals, and medical centers. AI/ML techniques include, but are not limited to, neural network models, deep learning, cloud-based services, advanced data analytics, business analytics, knowledge based systems, decision management, predictive analysis, sentiment analysis, natural language processing, machine vision, robotics, and expert systems.

2. Overview of Food Service Distribution Networks

The national food service system delivers food and supply products to almost 1 million customer locations, including chain restaurants, independent restaurants, schools, nursing homes, hospitals, convenience stores, and sporting events. Food service distribution networks include a large number of small, medium, and large distributors that provide a multitude of temperature-sensitive and shelf-stable products to end users, from restaurant chains with thousands of units to solitary local schools. Distribution centers receive food and supplies through long-haul refrigerated, frozen, and dry shipments from manufacturers and importers and redistribute these food products through truck deliveries to customer sites.

Food service distributors have developed a strong and efficient nationwide distribution network consisting of a large number of distribution centers, private-label manufacturers, stock-less DCs, sophisticated IT and telecommunication infrastructures, and a large group of trained drivers and sales representatives. However, this network design is currently going through a modernization process that optimizes distribution routes while minimizing costs, pickup and delivery windows, and energy use. Advances in technology allow for the systematic collection of vital information related to food service distribution. Improved temperature-control logistics have allowed food service companies to include temperature-sensitive products in their offerings. Continuous education and training allow food service distribution companies to automate, streamline, and optimize various operational aspects of distribution logistics.

2.1. Understanding the Food Service Distribution Ecosystem

Food service accounts for 51% of the total United States food expenditures and is extremely varied. Spend is broken down by 33% for limited-service restaurants, 22% full-service restaurants, and 13% for eating and drinking places. Food service provides key aspects of tourism and hospitality and provides meals for schools, hospitals, and other venues where consumers may not have private access to meal preparation equipment. While food service is not necessarily a large portion of a particular consumer's per capita meals, it provides diversity to consumer choices. The preparation and distribution of meals for this segment of the market is cyclical and seasonal. Pricing and demand can vary widely. Food service distribution is a complex public-private partnership linking myriad growers, packers, distributors, and manufacturers; all relied upon by millions of consumers and government entities.

Food service and grocery retail are similar in many ways, but very different in others. Food service is about meals and associated services; grocery retail is about products. Grocery retail provides high service merchandising, demand stimulation, and convenience. Food service has created products that are traditionally meal-oriented but may also be product-oriented with items such as pizza, grilled sandwiches, subs, and rotisserie chicken. Both have realized the power of deli-bakery to attract consumers. Both utilize category management techniques, streamline distribution, and use of fast-track distribution centers, but food service faces challenges unique to its delivery systems.

3. The Role of Artificial Intelligence in Food Service

1. Definition and Scope

The rise of the term “Artificial Intelligence” is associated with a conference held in the summer of 1956 at Dartmouth College. Speech recognition, language processing and robotics were among the initial challenges in AI. AI is defined as referring to a set of technologies that enable machines to perceive their environment and the context in which they are acting, learn from that context, and make decisions, in order to achieve a specific goal. These capacities give AI a particular potential for automation and affinities with other cutting-edge technologies, such as machine learning, the Internet of Things, robotics, big data and quantum computing. Machine learning, more widely used, seeks to provide the algorithm with a training set containing examples that, by similarity, enables the algorithm to deduce behaviors for other examples that were not present in the training set. Inside this logic, neural networks attempt to imitate large-scale real-time brain functioning. After the quantitative leap made possible with big data, the current “disruption” comes from the significance attributed to neural networks, particularly deep learning – which has become the most successful machine learning method in recent years. After dabbling in other business areas, AI has recently taken the approach of global solutions aimed at reducing web-based uses and users’ level of ambivalence with regard to brands.

2. Current Applications

In the area of food service, chatbots, used to assist users of online ordering systems, are the most visible form of AI. These chatbots can be simple, performing highly automated interactions that have a narrow objective, or more sophisticated, using AI techniques to provide a more natural way to interact. The AI used by travel agencies has long been applied to food distribution by companies specializing in e-commerce for the food industry. These food e-commerce portals use collection and access techniques, commonly associated with data mining, to observe behavioral patterns exhibited by their customers. By processing these patterns and analyses using algorithms conceived by these companies, food distribution companies can optimize their addresses for visits and predict future demands, such as the number of items requested in each product category according to the time of year and day of the week.

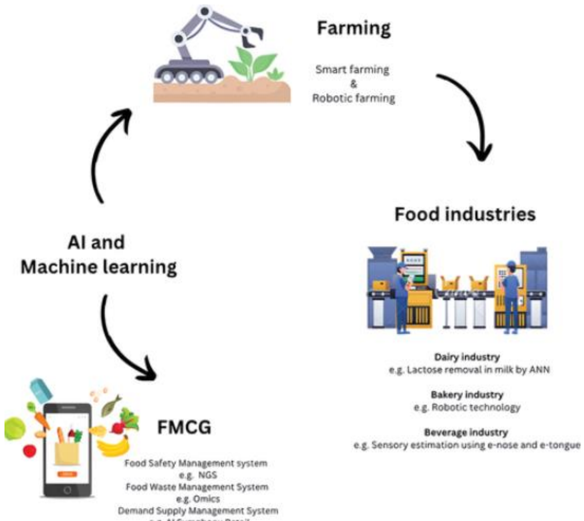

Fig 2 : Applications of artificial intelligence (AI) in managing food quality and ensuring global food

3.1. Definition and Scope

“Is it true that intelligent systems, able to learn complex models, predict effects and consequences of our actions using mathematical relationships, optimize our planning at different time frames, ensure a high probability of a correct solution, are key players in all business areas including food and meal distribution? The answer is evidently yes. In this chapter we elaborate on these issues and try to convince the readers that having AI as an operation without which business cannot be run is not an exaggerated position.” Food and meal distribution, not being a pioneer area in using intelligent system based solutions, clearly lagged behind other business areas in using Artificial Intelligence based solutions. It is not an easy task as food and meal distribution problems are simulated using simple methods. As a professor in the Operative Research area mentioned – “they are an “easy prey” for very simple planning tools that only simulate a part of the planning process, and are not able to give a full answer nor to give solutions in the short term when sales are unpredictable”.

Aggregated level planning, long time horizon, pessimistic sales forecasts, and no real supply chain management make this area a particular one in research as well as in business. The area of food and meal distribution has been for long years the main source of development of control theory. Moreover, Food Service Distribution is a unique area in that there are three different types of customers: school age children in public schools, mainly elderly in public welfare institutions where food is offered at discount or free of charge and all others who have to pay the real service costs. There are also important real operation aspects, which are the necessity to deliver hot meals early morning for lunch consumption and the fact that there are no storage rooms in meals consumption locations. These aspects make food and meal distribution activities difficult to optimize with any adequate level of quality, and multimode routing the only method to apply is a demand-driven centralized distribution.

3.2. Current Applications

The intersection between food service and AI has produced some early applications which point toward the strength of the technology in optimizing the distribution of food services, solving entrenched issues such as unreliable supply chains, outages, and waste. It is assumed AI will be used by a majority of fast food restaurants by 2030. Other industry insiders agree, predicting that, along with AI, robotics and sensors will be used to manage everything from drive-throughs to inventory ordering, increasing sales by 5-10% and reducing labor costs by 10-25%. AI and machine learning are already being embedded into mobile applications, such as for ordering, engaging consumers, improving visibility on time to order satisfaction, streamlining troubleshooting, building predictive, actionable reports for management. After much experimentation, a major coffee chain is introducing its AI ability to customize coffee ordering to the entire market.

These specific implementations continue to grow. As one quick service restaurant application puts it, "Every inquiry to customer service is a unique transaction based on each customer’s previous interactions, preferences, order history, and customer data shared throughout the company to make that specific customer experience unique." AI fulfills this daunting task, reacting to an annoyed customer reporting on social media of a bad delivery while quickly answering a customer on the phone with a different issue. Technology systems throughout the company tie together delivery and customer access to stores, access to app ordering, and input routing. It is recommended to embed AI quotes and ordering throughout the company in every useful distribution channel. Using publicly available daily temperatures, food safety and health tracking information, and by tracking a corporation's promotional events and other sales drivers, it easily schedules demand-driven delivery of up-to-date specialty food items to restaurants.

4. Machine Learning Techniques in Food Distribution

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly used as a part of large decision support systems which have solutions for the Data-rich sector. Over the last 30 years, AI and ML have been used in many decision-making settings in the food industry. Predictive analytics is when forecasts based on statistical methods of the future become the basis for various demand decisions. Optimisation algorithms can define specific action to achieve maximal net gain from operations. Such models can identify unique production decisions tailored to each demand hub within the distribution network. Technically, known as a "Demand Forecasts", such Delivery Demand requirements, one, three or six months into the future is commonly used in Resource Planning and Factory Scheduling Engines of manufacturing firms.
The term "Demand Forecasting" has slightly different meanings in the manufacturing and food service distribution world. In the world of manufacturing, Demand Forecasting builds predictive models with explanatory variables that drive demand magnitude and season change are determined. Retail displays, store specific variability, pricing and promotion programs, and secondary demand generators are some examples of input variables to such models. Analytical forecasting is successful because the forecasts are used by short term scheduling engines for factory operations. Demand Forecasting in the food service distribution world is to predict demand because it involves "calculating push" decisions. There are generalized probes, notably a model using a combination of multivariate models embedded in an algorithm, Dynamical Optimization Models, Seasonal-Cycle Model and a Neural Network Model, for example. Such exploratory Demand Planning models are however rarely used as a basis to make Delivery Demand plans for delivery hub level times for delivery routes and vehicle fleet.

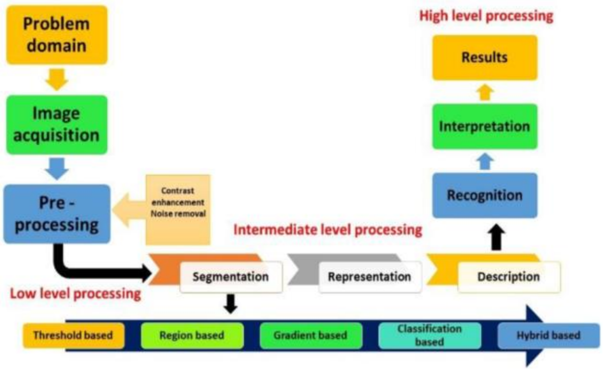

Fig 3: Machine Learning Algorithms and Fundamentals as Emerging Safety Tools in Preservation of Fruits

4.1. Predictive Analytics

The explosive demand for prediction techniques in various fields has caused the avalanche growth of prediction in the area of machine learning. Apparently, real-world applications except for some physical sciences, rejected the adoption of fundamental predictive systems and opted for ad-hoc approaches since they tend to perform better in practice. However, the recent revival of interest in the use of kernel methods as a unifying framework for non-linear prediction has provided a sound basis for their adoption. This new approach resolves several of the issues and limitations that finally led to the demise of classical kernel methods predicating their use in a small number of special cases. Moreover, the detection of some well-known problems associated with neural predictors, such as the mode collapse or the non-representative learned features, have relaxed the development of a unique hypothesis for generalizing to complex data. These presented issues arise in many other predictive techniques developed in the last two decades. As such, the current ability to accurately complementary solve these problems may be considered as an insurance for an increased use in practice of kernel techniques. Shortly, the algorithms used to manage the trade-off between prediction accuracy and cost.
In particular, for a collection of algorithms used, the practical observations are more evident when they are optimized to paradigmatically learn predictive problems. Examples of continual research on such optimizations are presented by the Kernel Adaptive Filtering, regression with Support Vector Machines, Bayesian Kernel Regression and Kernel Logistic Regression, among others. It is then not surprising to observe that there have been able to lead sizeable evidence in many different real application domains, such as speech and acoustic modeling, human-machine dialog systems, automatic recognition of natural languages, information retrieval, collaborative filtering, bioinformatics or biomedical applications of different natures, to mention a few. The doors for further predictive research seem wide open and only.

4.2. Optimization Algorithms

Management of food service distribution networks on a national scale should satisfy the basic condition to have the most right balance among the entities. Nutritional factors, economic factors and environmental issues have an important role in network balancing. Support of optimization algorithms can easily be an aid to achieve

overall national level objectives. GHG emissions constraints, lower density zones of the network, security issues, budgetary and financial guidelines can be some of the goals of optimization algorithms as a multi-level computer based decision supporting systems.
During the decades many tried to optimize the food distribution network by using optimization algorithms. The first scientific paper regarding a food distribution network was presented around the end of the 70s of the previous century. Many applied optimization algorithms in the food supply chain area since then. Food supply chain optimization study mainly used optimization techniques. Similarly, other works utilize the same methodology. Probably there exists no optimization study in any area as detailed as food supply chain optimization studies. All optimization algorithms try to minimize the costs of the solution while lacking in some constraints. Including as many constraints as possible to these algorithms as incentives makes it focus on the more realistic solution.
Most of the constraints in the area of food service distribution networks relate with nutritional and societal-order issue demands in the whole national area. Different historical periods may represent different phases of the whole model. For example, the Italian supply chain approximately commercialized the same amount of foods from the national market base, independently from the historical period. The consideration of some constraints is important while others might be eliminated when actualizing the algorithm for solving the computer based decision supporting system. Aim of those constraints would be asked to optimize: for a given set of restrictions a suboptimal food supply configuration will minimize the distribution costs.

4.3. Demand Forecasting

Demand forecasting plays a critical role in the functioning of food service distribution networks, such as cash and carry or wholesale type distributors. Accurate demand prediction allows for appropriate allocation of investment in inventory and fleet, and primarily leads to cost savings in said investments, as well as driving operational cost savings from a better balance of supply and demand in both transportation and stocking operations. However, demand patterns are highly variable because of demand surges at certain periods, price volatility, seasonality, changes in economy, and the number of holidays and cultural factors.
Traditional statistical models assume demand to have a linear structure, which is not the case in food distribution. For example, demand increases at certain times before holidays but does not peak at the day of the holiday, suddenly coming back down to trend after the event, while models such as exponential smoothing can lead to the overestimation of demand levels. Also, at some point within the considered time horizon, demand can change dramatically for long periods, which is poorly managed by classical demand forecasting methods. Considering that the models are based on historical data, they will generally not perform well for low-frequency products, which is the case of general food distributors, where many of their products only move once or twice a year.
Statistical demand forecasting models are based on the assumption that the future demand will be similar to the past. This could be true for stable demand patterns, but distorting demand patterns in the past or future can lead to highly inaccurate demand estimations. Therefore, it is important to include other data sources and information that may influence demand and drive demand forecasting methodologies away from being purely statistical. Machine learning models are great for transforming input data into useful representations to improve the stochastic demand forecasting process.

5. Integration Challenges

The implementation of Artificial Intelligence (AI) and Machine Learning (ML) in national Food Service Distribution Networks operates under regulations and procedures. Thus, integration must comply with current legal frameworks, including violations. Of equal concern is the budget that encompasses operational expenses as much as costs related to the initial investment for recruitment and training, infrastructure build-up, development, and support that ensure security and compliance.

1. Technical Barriers Possible drawbacks of ML models are the lack of understanding, or interpretability, that easily lead to skepticism or rejection of the model, especially those which are classed as "Black-box", those performing complex non-linear internal operations, such as Deep Learning and Neural Networks. Classically, the ML and AI domains have favored higher model accuracy over transparency, but explainable natural language generation and approaches are mitigating that burden, mainly thanks to the voice of the customer. For sensitive operations such as security and healthcare, legislation is acting upon the need for clearer ML model transparency.
2. Data Management Issues Whether data-backed or rules-based, AI and ML systems demand stringent and clear data governance, processes addressing all data lifecycles, including storage, utilization, and curation. Data must be secure, reliable, and available to integrate various data types of live and historical data, to be understandable and user-friendly, and to meet compliance and security requirements. Lack of clarity and organization throughout the organizations, in terms of processes, governance, and data engineering and quality, as well as the extent of the data which users will have access to, are key obstacles determining AI/ML application value and impact. Over-reliance on data which at some point may become unavailable, whether due to data privacy regulations, ethical reasons, or unavailability lately, and oversampling, known as "excessive", should be averted.

5.1. Technical Barriers

As examined earlier, different tools can aid the functioning of different distribution networks. However, there are still certain barriers – barriers that do not account for general AI. There are no tools or models that could allow an automated training of any model so far. Afterwards, a formally defined goal – or satisfaction function – should be created, and the AI should then complete the job and find the optimal solution, just as humans do. With presently available tools, the process is in practice still supervised learning with humans involved in the training and/or in the toolchain. Furthermore, two problems that still constitute an obstacle in automating the training of models, and they are important both in research and practice. These generic problems must necessarily be solved when or before creating a tool for automating machine learning.
In brief, the first problem deals with appertaining data to the appropriate class, namely "normal", "anomaly", or "not available" (unlabeled), for solutions of a multi-class problem; with merging all the data sets divided in different classes (possible distributed) with different time resolutions; adding the available meteorological data; calibrating the creation of the appropriate flow profiles; including the time of the day, the day of the week, and the day of the year in the model; etc. The second problem pertains to optimizing the training of – or the prediction made by – the model. This concern for optimization (not for accuracy or prediction error) should apply to hysteresis, numeraire, distinguishing rates of values between actual and predicted, cost definition, and so on.

5.2. Data Management Issues

Decisions in NSFDN are mostly catered based on the aggregated demand either by using district level need, internal need of different Food Distribution Institutions or the overall need of the state. The process of integrating Artificial Intelligence and Machine Learning to more granular and specific decisions have some challenges related to the availability of data. One troublesome matter is how to clean data in an automated way, especially if data mining is done for heterogeneous sources. For more advanced methods, data is needed to be available from different regions, and how to pool these different data is a further challenge. Who owns data is another matter for discussion: who saves and who benefits? The third concern is the generalizability of conclusions based on the results of historical data analysis, also considering the different institutional, cultural, and other settings.
Real-world decisions are frequently different from what is predicted by the best-designed model because of the local issues that were not included in the model. This is especially relevant for food security. Other typical data management issues arise in the implementation phase. Actually, the digitalization of FDI records does not ensure unified data since the individual format of banks, insurance companies, and tax offices does not guarantee the coherence and harmonization of FDI identification codes. Lack of documentation about historical data and many versions of similar sources does not ease the data homogenization in different quarters. This is a typical problem when using Notarial services as collocation and transaction costs do not hinder informal agreements. Finally, the challenge is how to transmit the model results to the decision-makers. For example, how much data is needed to request from AI/ML systems to convince stakeholders of the digitization of the lending process – and how long should this take?

5.3. Regulatory Compliance

One of the distinguishing features of the national food service distribution sector is the heavy burden of regulatory compliance, including health, safety, quality, and operational codes of practice. This has evolved over many decades, impacting just about every part of the product order, transport, availability, storage, temperature monitoring, delivery, back-office systems and practices. Whenever an innovative technical capability is introduced into this process, the regulatory burden is magnified. This is relevant here since many of the innovative technologies that are considered disruptive right now are not only going to affect what products get delivered and when but the underlying implementation technology. Both hardware – delivery by fleet, drone, air-taxi, and the rising pressure for less truck emissions – as well as the predictive back-office AI engine are of significance. So the research on the historical burden and any new proposed introduction must also include what added problems or relief these new technology drivers are proposing to comply with.
Indeed, the traditional and perceived wisdom to innovation at a national level, adopting a least-cost strategy, is not only sector-dependent but becoming more apparent and dependent on the historical burden. One can rejoice in the success in numerous sectors that have reduced the regulatory burden, but at what cost? For instance, without regulatory burden for IIT, how long before fake news and verbal scams on national governments, as detected in previous elections around the world, permeate through the business sector? Without developing adequate regulatory compliance within digital economies, how do we ensure that only compliant AI models, that are aligned and verified through clinical governance, are legally binding and can be drawn on in court claims?

6. Impact on Supply Chain Efficiency

The economic impact of food service distribution in the US is measured in trillions of dollars and millions of jobs. In addition to economic interests, food service distribution has profound impacts on national security due to its provision of supplies to key military locations, and on health due to its delivery of nutrition somewhere between 20% and 50% of the time. Disruption of food supplies can create shortages and initiate insurrection activities. Federal agencies are therefore keenly interested in the development of a resilient food service distribution system with the help of AI and ML.
The question arises as to what type of impact is potentially achieved through the introduction of advanced algorithms for food service distribution. Supply Chain Efficiency might be checked first before attempting to quantify economic effects. SC Efficiencies are determined on the basis of three key performance indicators, Cost, Time, and Quality. Cost is a traditional performance indicator and is considered the most important with the current competitive situation in food service distribution, especially given increasing profitability pressure; Time is considered as a significant impact area; and Resource Allocation is a non-traditional and novel but very promising indicator which explains "what-science-or-technology-is-doing-for-whom". Food service companies would require hard data to achieve evidence of their contributions to their stakeholders and would make better decisions on use of funds if they would receive a clearer picture from the funders' perspective.
The development of really efficient algorithms is a technical area of a high potential gap due to the difficulty of dealing with real-time evolution of parameters, and, even more importantly, with meta-heuristics. Indeed, these trendy tools can provide a great resource allocation and great outcomes which would help decision makers and make a large contribution to SC Efficiency.

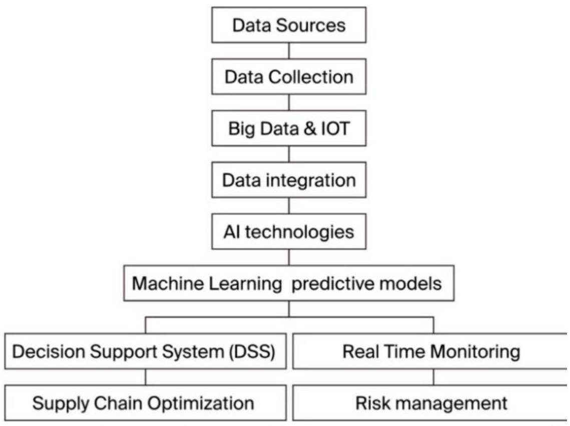

Fig 4: Enhancing Supply Chain Resilience Through Artificial Intelligence

6.1. Cost Reduction

The food industry is characterized by close interaction with multiple supply chain partners, being subjected to marketing demands, such as quick response time, price stability, ordering quantity flexibility, and demand forecasting. These marketing demands from distribution partners could not be satisfied without consideration to costs associated with order transportation and replenishment from upstream partners, especially in the present era of ever increasing market competition. Any technology that promises to reduce distribution costs and improve cash flows of distribution partners must necessarily be considered for implementation. Logistics within the food industry is characterized by recurring deliveries of temperature-sensitive products. Mechanisms are now available for using this information to reduce costs associated with variable demand for which unclear demand drivers result in large variability in ordering patterns and supply channels. Final customer demand function for perishable products that fluctuate widely could be set to limit demand for some position on product sales curve to levels tolerable by production, inventory, and supply chain cost reduction without diminishing utility levels of final customers. It is difficult and costly for food chain partners to make and implement agreements. It would be useful if each food chain partner could use information about demand and cost such that cost reduction and utility objectives could be accomplished. The food chain would have continuous on-line demand, replenishment scheduling, and pricing decision capabilities. As new considerations could be provided frequently, partners would know how to minimize cooperative costs. In doing so, both customer needs and best partners could be identified. Remote temperature monitoring allows for distribution partners to immediately respond to temperature excursions.

6.2. Time Management

Timely delivery and efficient service are vital components of the food service distribution process, which consists of the storage and transfer of supplies to food service entities. Despite being able to support their customers 24/7, food service distributors can sometimes delay delivery due to high volume time periods and contingencies. AI and ML can be utilized to prevent delayed delivery and lost customers. Food distributors rely on human forecasting to predict volume increases and build additional resources to handle order flow, which can bind large quantities of resources for periods of time at high costs. AI and ML automation can be used to predict increased order flow demand with high accuracy. Based on the prediction, food service distributors can use neural network optimization to calculate the best way to manage their resources and asset valuations before the actual demand load.

These models can analyze data from different providers and source actuaries to cover a percentage of the risk posed by demand shocks while continuously recalibrating. AI and ML models manage the storage network to determine throughput capacity and movement parameters based on food types and proximity zones, as well as the best means of transportation based on an optimization model that uses fuel prices and distances to derive the lowest cost means of transportation. Automation makes demand and route forecasting and storage management logical. Time is a crucial component of the total cost of food distribution. The longer it takes to deliver, the more costly it becomes not to mention the reputational and customer loyalty damage. AI and ML of automated data tell not only what to truck when but when to start based on proximity, weather, and distance to travel – also automatically scheduled. These models cut loss because customers are not willing to pay, do not take delivery, or take delayed delivery. If the customer is willing to change products based on urgency and routineness of food items, better modeling predicts what can go on the trucks scheduled for when. It also determines what value can be assigned to seasonal, limited, or commodity foods as alternatives on a truck with other products to incentivize buying.

6.3. Resource Allocation

Food service distribution networks (FSDNs) face difficulties in managing supply. Solutions to this problem often involve building new warehouses or closing existing ones. Artificial Intelligence and Machine Learning (AIML) can solve this problem by recommending allotment, predicting demand for sales and products, recommending special scenarios for holidays and special events, planning a distribution network, planning stock and warehouse facility layouts, recommending and managing logistics service providers, capacity planning, vehicle routing, order and inventory management, and reverse logistics. Thus, it is possible to solve different FSDN resource allocation problems by using AIML.

AIML can be used to solve a variety of resource allocation problems in FSDNs. They include capability planning at the micrologistics level by recommending and managing logistics service providers, vehicle routing by capacity planning solving problems, order and inventory management used for a just-in-time system at the base of FSDN resource allocation, reverse logistics problems, and capacity planning at the macrologistics level. In short, AIML can facilitate decisions on how to most effectively utilize available FSDN resources to meet customer requirements by minimizing costs, maximizing profitability, and/or balancing demand and capacity. Decision process goals related to FSDN resource allocation include efficient sorting, storage, consolidation, windowing, pick-up, and distribution of food service products in a timely manner at the lowest total costs.

Optimal routing of food service distribution visits is significant for ensuring customer service requirements are met at minimum total costs. Numerous constraints are involved. Variable time windows can be identified for visits and included, as well as constant windows, and driver and vehicle constraints. Solutions consider routing only or routing and facility allocation. Routing with constant time windows is a complex, special case of scheduling identical parallel machines, and vehicle routing and scheduling even with soft time window and service duration constraints, is NP-hard. Furthermore, simply adding a polynomial number of time windows to a problem formulation can result in an increase in solution time with solutions possibly remaining inaccessible.

7. Future Trends in AI and ML for Food Distribution

Because of a series of major world developments—COVID, international conflicts, inflation, and climate change, as a few factors—it is clear that not only in the food services sector but in many industries, flexibility is key. In the food services sector, which includes centrally located warehouses or regional distribution centers, addition of satellite “express” distribution centers or models of foods prepared locally then "merchandised" for final preparation onsite, with the consequent need to be open to very abrupt changes, may need to be developed. Recent years have underscored that models built to predict a range of values corresponding to climatologic conditions, market trends, diseases, and similar external drivers can go off the rails, and cannot be the basis for “set and forget” models for business decisions. Using state-of-the-art AI, ML, and other forecasting tools could certainly help develop these insights, but only if regularly updated with external data.

Fig 5 : Enhancing Food Integrity through Artificial Intelligence and Machine Learning

Since the e-commerce boom due to the pandemic has exposed weaknesses in the existing logistics distribution models—excessive lead times, especially for perishables—future distribution networks will likely include "last mile" hubs, with additional stocking distribution centers and satellites only responsible for consumer order aggregation and fulfillment. But while plenty of investors and consultancies are presenting apparent solutions built on other industries' experiences, the food service distribution sector poses challenges that will need deeper consideration and positing thinking—a need for extensive knowledge of the underlying product characteristics, in particular for perishables; and a need to guarantee compliance with hygiene, shelf-life, and liability considerations.

7.1. Emerging Technologies

Researchers and businesses are actively exploring the fusion of cutting-edge technologies with artificial intelligence algorithms and machine learning systems for data analyses and utilization in different areas. Their focus is on potential collaborative advantages gained in operations, commercialization efforts, and product services. This has given birth to many new technological applications and innovative services. For instance, blockchain systems verify data through smart contracts, eliminating the need for auditors while ensuring credible data sharing. AI services are increasingly conducted through the cloud. The distribution area is also beginning to utilize augmented reality and digital twins. Predictive data analytics is increasing product perishability transparency. The Internet of Things is facilitating the digitization of products and services by embedding sensors into the service ecosystem. Robots are conducting last mile deliveries while drones are being tested for inventory replenishment, customer deliveries, and even restaurant and shop surveillance.

With the delivery area of food service distribution becoming increasingly competitive, last mile performance must be optimized. There are many new technologies emerging for these services. It is evolving quickly as products offered change and new technological challenges and applications develop. These physical and operational distribution developments will be examined in future research. Emerging technologies where these new transactions and activities will be developed include: blockchains, which validate and verify transactions among service partners and provide transaction transparency throughout the entire operating service distribution chain; the cloud; augmented reality and digital twins; predictive transparency; data-embedded products/IoT; robotic deliveries; drone deliveries; new mobile methods; vertical farms; sustainable packaging; automated restaurant systems; and redefined sold services. Food service distribution solutions integrating AI with these technologies will especially be examined for longer-term distribution operational strategy planning.

7.2. Sustainability Considerations

Sustainability has become a pressing topic on a global scale, as several industries, including food distribution, are amongst the highest polluting sectors. As such, there is immense pressure from within and outside businesses for change towards mitigating aforementioned impacts. The potential for AI in capturing, monitoring, and making use of sustainability measures is somewhat underexplored as a whole. Most of the research in the area seeks to solve practical problems, instead of exploiting the potential of AI in acting as an enabler for change. Moreover, the vast majority of capabilities on offer is actually in external consideration. This can be chalked up to the mere fact that the actual effect AI has on sustainability is really difficult to measure, as there are several variables related to core organizational practices, changes in business and societal structures, uncertainty, and competitiveness influencing the relation. However, as businesses are becoming confronted ever more with the need to be more transparent, the interest in internal considerations is increasing. If proper data on sustainability-oriented internal processes were available, there is the potential to have AI services focused more on making explicit the impact AI can have on considering sustainability in decision-making.

The increased presence, focus, and change towards sustainability have had a massive impact on how environments are considered in developed economies. They made businesses explicitly include their environmental impact and responsibilities in their decisions around corporate social and ecological responsibility strategies. It is becoming ever more common to see customers and buyers use sustainability of products and services as a decision variable. In the end, the investment in training the AI may prove beneficial, as software services enabling consideration and transparency of sustainability in decision-making are becoming more common.

8. Ethical Considerations

In several areas of the world, including most of Europe, the United States, and Brazil, there are laws for the protection of data, especially concerning personal data, which have to be correctly implemented in projects where it exists the possibility to share personal data or those that can indirectly identify individuals: tax ID, email address, name, and surname, among others. The collection, organization, storage, processing, and dissemination of personal data together with other pieces of information can generate risks to the property and rights of individuals. In addition, digital platforms' privacy policies can be too broad, allowing companies to collect, store, and share more information than necessary. Organizations, before scoping a specific dataset to be used by models for learning and prediction, must take into account not only ethical responsibilities but also privacy-related responsibilities that depend on the geographic location where the project will be applied.
Another ethical responsibility refers to algorithm bias that can be ignored in models and algorithms because predictive tools learned from historical data used for training might learn a preference for people that are privileged, whereas people from disadvantaged communities who have different features from those that were privileged might be harmed. The machine learning automated decision-making process might result in segments of a population being unjustly treated. For example, in the justice area, if a predictive model is trained with a dataset in which there exist many ex-offenders, and few people who did not recidivate, that model might predict recidivation for a person from the minority not having previously committed any crime (the person was unjustly treated by the algorithm). Therefore, avoiding algorithm bias is an ethical issue that has to be considered by decision-makers.

8.1. Data Privacy

In efforts to create unbiased machine learning models with higher predictive power, researchers have moved towards using bigger and bigger datasets. In doing so, they have often turned a blind eye to privacy implications of their research. In particular, specific Food Distribution problems like Food Routing within cities, Food Waste Prediction using Climate Data, are using city-wide climate, traffic, pollution and food routing to glean information about both what food individuals tend to consume and where they tend to buy the food from. The dangers in using Prediction Models on Classifying Unseen Areas like Undisclosed Customers with Unconfirmed Labels and Destination Class Labels are explicitly highlighted. In contrast, our approach attempts to fix the limitation by only providing food recommendations for an area with positive food sales and rely on historical sales data on the food truck to perform customer segmentation. Further, to protect the Food Truck's Customer Privacy, we applied Non-Negative Matrix Factorization with Hierarchical User-level Data Augmentation with Infrastructure Prior Integration, to provide address-level demand information for utility optimization.
Answering privacy concerns, we use Vectors Not Matrices to only store demand summary at the introductory phase of the road network design, and only update the summary using counts of demand for known locations to save space, after the previous summary is not efficient anymore. For instance, 100 Small and 100 Large Food Trucks with unique daily demand/space requirements can be approximated to save 376,370 bytes. Such methods can allow millions of hires to be accomplished without having more than a few megabytes of data on the candidate/employee. Further, using Differentiable Information-Aware Neural Network Training, we can glean layer-wise priors based only on matrix factorization and retain them for the workers' encoder, since bounds can be determined for schematic and categorical data. Privacy as an Ethical Consideration is interesting given that Provision of Economic Stability is one of the goals of AI/ML in the Public Sector.

8.2. Bias in Algorithms

Algorithms coded in AI systems can suffer from problems not inherent to the machine, but based on their coding or the data inputs. If a model is based upon incorrect data or coded improperly the outcome will be biased. Racial, ethnic, or gender bias in an algorithm can create skewed results that can continually disadvantage these groups. The prediction of risk scores in criminal justice algorithms can lead to extended time periods of incarceration for innocent people. The AI based recruiting algorithm was found to be negatively biased in searching for applicants who were women, and was therefore not used following its discovery. These models must be carefully examined for bias prior to use because of the consequences they can generate.
Racial questions about facial recognition technology have appeared most visibly in policing and surveillance implementations of the technology and have disproportionately affected certain racial and economic groups. This technology had higher rates of false positives for certain faces, and products with lower rates of false positives for these groups often also had higher rates of false negatives for these demographics. Both the higher false positives and false negatives are troubling. The policing implementations of this technology have a long

documented history of misidentifying innocent individuals as violent criminals. A study reported that because of inconsistencies in data about how many requests to police facial recognition technology made about the innocent population, it was difficult if not impossible to calculate what percentage of false positives occur in the use of facial recognition technology by police, but a sample data set from two police departments suggested that the false positive match rate might be as high as 98%.

9. Conclusion

This work presented the unique nature of food distribution, particularly of perishable food distribution for our schools and the unique challenges it faces. The work discusses the importance of determining the best network designs to satisfy requirements of both cost angle and service angle, as service efficient operations would help ensure deadlines are not broken, leading to lack of nutritional needs for the children. This work further discusses how these systems have been operating to this day and the introduction of technologies like AI and ML are now set to make operations even more efficient. Integration of AI and ML into food service distribution systems can and will support improved order fulfillments, reduce carbon footprints, minimize waste, help save money, help save time, and eventually interests of students are met through healthy, locally purchased foods. What has, and will support successful implementation of those technologies into the food service distribution world is its uniqueness: food service distribution systems exist to serve the interest of students. School and school districts are doing the work they are doing to make it a better world for kids and care about making it better!

Future studies can potentially look into making these models more robust by integrating additional challenges schools or school districts face in their day-to-day decision making. Further research in public discussions to encourage the food technology world to align itself to ease the food distribution world to uplift its efficiency. As well as developing additional models into finding better facility locations connecting school districts to food distributors to further optimize both overall models.

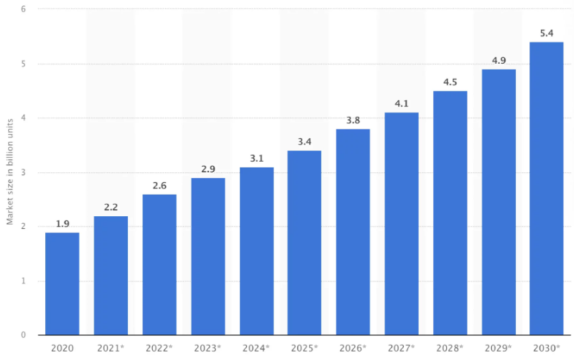

Fig 6 : AI in Food Industry

9.1. Summary of Key Insights and Future Directions

AI and ML techniques have a strong potential to develop decision support systems in a complex and ill-structured domain such as the NFSDN. Such techniques can help in the more accurate and timely prediction of demand and the supply of food items and the drivers of variability, thus improving the quality of decision making. Furthermore, they can help in the identification of novel and more profitable food sourcing solutions. Additionally, they can lead to the more consistent and optimal assignment of distribution vehicles to routes and physical depot locations, often by considering schedules of evolving demand levels and queues. Finally, they can help in determining a fleet of distribution vehicles that improves resource utilization and reduces carbon emissions while minimizing both infrastructure and operating costs. We discuss the specific capabilities of AI- and ML-related techniques with respect to the key decision-making areas of the NFSDN. Furthermore, we provide recommendations related to the choice and combination of AI and ML techniques for enhancing capabilities across each decision-making area.

We conclude with a discussion of future directions for the application of AI and ML to key decision-making areas. Specifically, we recommend interdisciplinary efforts to combine knowledge-based and data-driven approaches. We explore the roles of explainable AI and ML as well as causal inference-based ML in improving the quality and transparency of key decisions related to the NFSDN. Moreover, we call upon NFSD industry practitioners to collaborate with AI and ML researchers to address potential model deployment challenges. Finally, we advocate research about emerging AI and ML capabilities with respect to the development of user-oriented and sustainable NFSDNs.

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