Big Data enabled Real Time Cold Chain Monitoring in A Container Port

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Abstract- *Domain adaptation is proposed to deal with the challenging problem where the probability distribution of the training source is different from the testing target. Recently, adversarial learning has become the dominating technique for domain adaptation. Usually, adversarial domain adaptation methods simultaneously train a feature learner and a domain discriminator to learn domain-invariant features. Accordingly, how to effectively train the domain-adversarial model to learn domain-invariant features becomes a challenge in the community. To this end, we propose in this article a novel domain adaptation scheme named adversarial entropy optimization (AEO) to address the challenge. Specifically, we minimize the entropy when samples are from the independent distributions of source domain or target domain to improve the discriminability of the model. At the same time, we maximize the entropy when features are from the combined distribution of source domain and target domain so that the domain discriminatorcan be confused and the transferability of representations can be promoted. This minimax regime is well matched with the core idea of adversarial learning, empowering our model with transferability as well as discriminability for domain adaptation tasks.*

Keywords- Container, Ports, Port logistics management, Cold Chain Logistics, Internet of Things, IoT enabled cooling system, RFID, Remote monitoring and controlling of containers

I. INTRODUCTION

DUE to the rapid development of computing power in the past few years, deep learning has achieved great improvements on massive machine learning tasks [1]. Despite the powerful representations learned by deep networks, most deep learning methods require large-scale labelled data sets and cannot handle unexpected situations with novel instances [2]– [4]. In other words, they are weak at transferring learned knowledge to new environments. Usually, a small change in the training domain may result in dramatic variation in the test Manuscript received March 13, 2020; revised September 23, 2020 and March 1, 2021; accepted March 31, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 61806039, Grant 62073059, and Grant 61832001; and in part by the Sichuan Science and Technology Program under Grant 2020YFG0080. (Corresponding author: Jingjing Li.) Au Ma, Jingjing Li, Kee Lu, and Heng Tao Shen are with the School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China (e-mail: lijin117@yeah.net). Lei Zhu is with the School of Information Science and Engineering, Shandong Normal University, Jinan 250358, China. Color versions of one or more https://doi.org/10.1109/TNNLS.2021.3073119. Digital Object Identifier 10.1109/TNNLS.2021.30731

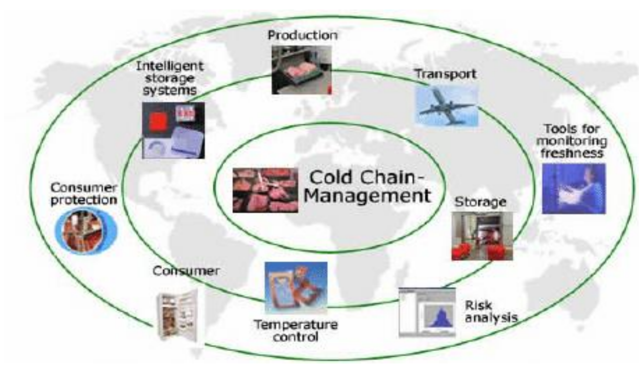
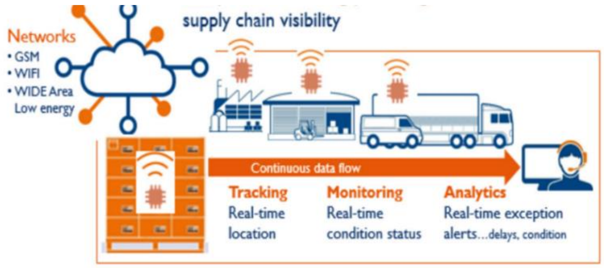


Fig. 1. Intuitive illustration of domain adaptation and the principle of maximum entropy. Domain adaptation methods devote to reducing domain shifts between the source and target domains. Actually, domain shifts mean the discrepancy between two distinctive distributions. As shown in the top of the figure, the distributions of the two domains become “close” after adaptation. The bottom presents an assumption with the principle of maximum entropy [7] applied on domain adaptation tasks. Suppose that there is a distribution under domain-invariant features, and the best model that can represent this distribution is the one with the largest entropy. This assumption fits for mechanism of training discriminator in adversarial learning. domain [1], [2], [5]. However, in many real-world applications, we need to label samples from an unlabelled target domain using labelled source data that have a different distribution from the target domain.



II. OBJECTIVE

Products need to be watched over when being kept in cold storage. Products that require monitoring are examined regularly. However, we are unable to check on all items every day. For assessing the items and identifying their state depending on a few factors, web-based support is required. This web-based assistance does calculations using datasets, applies predictive framework algorithm, and provides useful information that can be utilized to advise the customer who placed their items in cold storage to remove it as soon as possible. Due to the client company's inability to track the items that are stored, this might help the clients identify which products from storage required to be processed first. When a bulk order is received, it must be examined. The bulk order must be divided up into variously labelled data. These labelled data are then swiftly further categorized using the algorithm developed for the project. There are certain things, nevertheless, that fall outside of all categories. This has to be carefully evaluated and manually classified. Our algorithm also identifies unique products like that and analyses that too based on the data calculations and manually deciding which category it should go in. Every day, the items must be inspected for any potential safety issues. To avoid causing harm to the products, any areas of concern about product safety must be quickly corrected and updated.

III. LITERATURE SURVEY

Literature survey was conducted as a current literature such as Web of Science and Scopus. Today, digitization is at the beginning of the main trends of maritime transport and port development (Yua et al. 2020; Cal et al. 2022). Different areas of work of the ports are being carried out within the scope of digital transformation (Zilch et al. 2019; Cal et al. 2021a). Agnatic and Kolanovic work on improving the quality of quality of services and factors of quality on a daily basis to the analysis of digital technologies applied at ports (Agnatic and Jovanović 2020). Although digitalization occurs in different ways in the literature, it is used in the form described by Gartner in this article (Gartner, Inc.2022). Within this framework, digitalization forces us to develop a new business model by changing the business model (Cal et al. 2021b). The components of Industry 4.0 are autonomous vehicles, robotics, artificial intelligence (AI), big data, IoT, digital security, and include important topics such as 3D printing (Cal et al. 2021c).

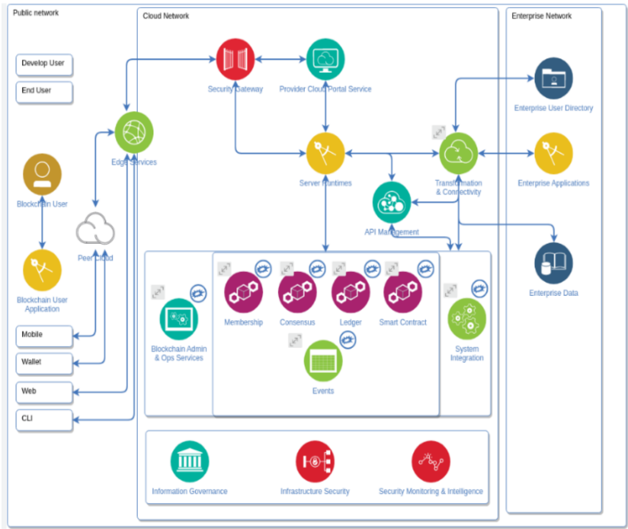
IV. EXISTING SYSTEM

The only extensively used technique for storing perishables in bulk between manufacturing and marketing processing is cold storage. By regulating the temperature and humidity within the storage system, it is one way to keep perishable goods in a fresh and complete state for a longer length of time. It is crucial to maintain a sufficiently low temperature since product will suffer chilling damage if not. For most perishables, the storeroom's relative humidity should be maintained at 80% to 90%; any lower or higher has a negative impact on the produce's ability to stay fresh. If kept at typical harvesting conditions, the majority of fruits and vegetables have a relatively short shelf-life following harvest. When it comes to monitoring items, sophisticated tools are required to track them as well as ongoing observation. Large organizations thus perform considerable surveillance. In cold chain logistics, it is also widely utilized in container trucks that transport goods over great distances.

V. PROPOSED SYSTEM

Since the customer may typically keep any kind of goods in a cold storage facility, the products are categorized into different labelled data. So, it is necessary to study the goods first. It is vital to evaluate whether the storage can hold the products before examining the items that need to be kept since storage facilities need to have vacant space for product storage. There will be certain special items that, once the products have been categorized, cannot fit into any of the categories since each kind of product requires a particular kind of facility. For instance, because medicinal items require ideal temperatures, we cannot keep them in food storage. To keep distinct items in the facility, specific solutions are required. An algorithm assists in separating out the goods in a client's order that are unique, deciding whether to save them or not depending on certain criteria. All items are promptly inspected based on predictive algorithms after being sent to the appropriate storage facilities, and some variables that are necessary to assess the product's state are calculated. Using our project, it may be completed instantly and automatically.

VI. ARCHITECTURE DIAGRAM



VII. MODULE DESCRIPTION

MODULE 1-CLIENTS

In this module the clients will register their details about their company name, address, contact details, contact person's email id and phone number and license holder's name. After admin checks the details and approves the client details a password is sent to the client via email. Using the password clients can login and register their quotes for storing the products. After that clients will receive and email regarding their quote status and can see in quote check menu. After that, client will upload the order details using the quote number. Client will receive a payment from admin regarding the order that is going to be stored in storage. Client then pays the amount for the order they uploaded. After moving the products into the cold storage, the clients can see the status of the products in the product status.

MODULE 2: COMMODITIES

In this module the commodity manager of the cold storage company will register their details for verification to Admin. After admin accepts the commodity manager details, the password is then sent to the manager, using the password, manager login the module. The commodity manager first checks the quotes from the clients to know whether the products can be stored or not in the storage, after accepting the quote, then moves to the classification of order products, where products stored inside the cold storage needs to be classified first. After classifying the order, the unclassified products which are the products that are unique in the orders are easily identified and classified manually based on the nature of the product.

MODULE 3: FOOD PRODUCTS

In this module the food products from the client are separated into many types of food products automatically for each order from each client. The details such as loss quantity, loss percentage, quantity in fresh, etc., all are calculated whenever we open the module. The routine check can be done for all the products by the food manager. The agricultural products, animal products, dairy products, beverage products, fruit products, vegetable products, processed food, nuts and spices and other groceries. All the food products are classified into these types, if the products are unique, it will be sent to other groceries. The details such as loss quantity, quantity in fresh and freshness of the product is calculated.

MODULE 4: PHARMACEUTICALS

In this module the pharmaceutical products from the client are separated into many types of pharmaceutical products automatically for each order from each client. The details such as loss quantity, loss percentage, quantity in fresh, etc, all are calculated whenever we open the module. The routine check can be done for all the products by the pharmaceutical manager. The vaccine products, tablet products, antibiotic products, antiseptic products, biologic products, sterile products, antitoxin products, antigen products and other pharmaceuticals. All the pharmaceutical products are classified into these types; if the products are unique, it will be sent to other pharmaceuticals. The details such as loss quantity, quantity in fresh and freshness of the product is calculated. Product is checked and results are shown.

MODULE 5: CHEMICALS

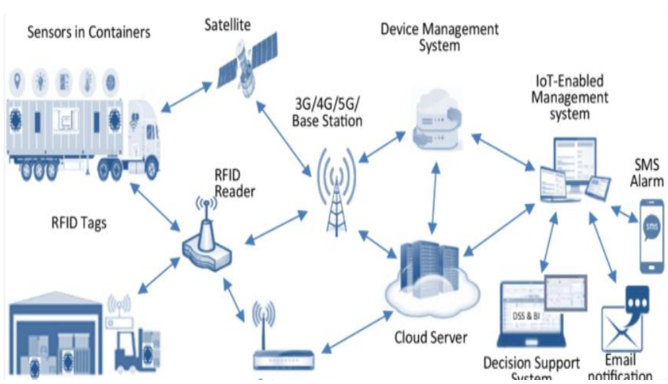
In this module the chemical products from the client are separated into many types of chemical products automatically for each order from each client. The details such as loss quantity, loss percentage, quantity in fresh, etc, all are calculated whenever we open the module. The routine check can be done for all the products by the chemical manager. The organic chemical products, inorganic chemical products, flammable chemical products, powder chemical products, toxic chemical products, radioactive chemical products, refrigeration chemical products, household chemical products and other chemicals. All the chemical products are classified into these types; if the products are unique, it will be sent to other chemicals. The details such as loss quantity, quantity in fresh and freshness of the product is calculated. Product is checked and results are shown. These details can be simultaneously shown to the client. Also, routine check is done based on checklist that has to be done daily or weekly based on the requirement needed for them.

MODULE 6: ADMIN

The admin checks the information of registered details from the clients, food managers, pharmaceutical managers, chemical managers, commodity managers and allows only the verified people by sending an email to for login the modules. They can check the status of their registered details in the view option. Admin authorizes the quotes sent by client, authorizes the orders and sends the pay slip details to the client. Admin then processes the payment reports and send the approval of moving the products to cold storage to the commodity manager and indicates the clients that their products are being moved to the cold storage.

VIII. IMPLEMENTATION

1. Make sure that the temperature of the cargo is within the range that's acceptable. Sensors are also used for sudden changes.
2. Temperature-related load rejections will be minimized. Costly spoilage will be reduced and redelivery costs will also be cut.
3. Critical reports will be provided for determining the location and time.
4. Data can be read from fuel sensors and alarms will be sent in case of fuel loss or threat. Improper fuel invoicing must be detected and resolved and unnecessary wastage must be avoided.
5. The mileage and engine hours must be tracked so that engine maintenance is decreased. Moreover, trailer lifetime can be increased as well.



IX. CONCLUSION

We propose in this article an interesting conclusion that it is better to prevent the classifier from getting too "confident" of the joint features. Thus, we try to maximize the entropy of joint features learned from both domains. In our work, we deploy both entropy minimization and maximization in an adversarial regime for unsupervised domain adaptation. The entropy minimization regularization gives the classifier more discriminative ability, whereas the entropy maximization regularization empowers the discriminator with more transferability. The proposed minimax entropy can be embedded into a conditional adversarial network to help feature learner extract domain-invariant features.

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