Intelligent Deep Fusion Network for Anomaly Identification in Maritime Transportation Systems

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***Abstract*—This paper introduces a novel deep learning architecture for identifying outliers in the context of intelligent transportation systems. The use of a convolutional neural network with decomposition is explored to find abnormal behavior in maritime data. The set of maritime data is first decomposed into similar clusters containing homogeneous data, and then a convolutional neural network is used for each data cluster. Different models are trained (one per cluster), and each model is learned from highly correlated data. Finally, the results of the models are merged using a simple but efficient fusion strategy. To verify the performance of the proposed framework, intensive experiments were conducted on marine data. The results show the superiority of the proposed framework compared to the baseline solutions in terms of several accuracy metrics.**

***Index Terms*—Convolution neural network, decomposition, maritime data, smart and secure transportation systems.**

I. Introduction

MARITIME data analysis has been intensively studied in the last two years [1]–[3], and different deep learning methods have been used for this purpose [4]–[6]. The behavior of maritime vehicles/objects can be represented using different data representation models including **time series** that are represented by a set of observations indicating the speed of the objects at different time intervals, **images** that are represented by capturing different frame videos, and **trajectories**, represented by different Spatio-temporal sequence AIS (Automatic Identification System) data. Ship data analytics involves examining different contextual conditions influencing the behaviors of ships. In this context, the goal is to learn the different abnormalities in ship data including time series, images, and trajectories, and under different conditions such as harsh weather conditions (strong wind, heavy rain, storm, etc). This is to support planers and managers in making decisions related to future movement directions.

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A. Motivation

Previous lines of research [6]–[8] have been conducted to develop different solutions for maritime anomalies whose detection is crucial for different entities from the maritime sector. The anomaly detection problem, in this case, consists of finding vessels that behave differently from the majority of other vessels. These techniques are based on both classical methods and deep learning models for outlier detection. They consider the whole maritime data for building the learning models. This degrades the overall performances particularly for large and diversified maritime data, where the data variation is high during the entire year. Decomposition methods have been recently shown a great interest in outlier detection community [9]–[11]. The idea is to build more focused deep learning models rather than one generic model hard to be trained in large and big data. Indeed, the decomposition methods split the data space into different regions, each of which contains similar data. The deep neural model is then able to train each region separately and then increase the model precision.

B. Contributions

This paper deals with the shortcomings of the existing literature of anomaly detection methods in handling maritime data and proposes a new framework that enables handling large and big maritime data for retrieving anomalies. The main contributions of the paper are listed as follows:

1) We explore a decomposition strategy to split the data into similar clusters before plugging it into an improved convolutional neural network (CNN) model.
2) We develop a simple, yet efficient, merging strategy to fuse the different outputs of the trained models and accurately detect the outliers.
3) We test the proposed solution on two traffic flow data and well-known maritime data, MARVEL. The evaluation is performed using different metrics for anomaly detection, and the results show the clear superiority of the developed solution compared to the baseline methods.

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C. Outline

The remainder of the paper is structured as follows: Detecting anomalies in traffic flow data in an intelligent transportation system is discussed in Section II for both marine and urban traffic flow scenarios. Section III introduces the developed framework with its main features. Section IV presents the experimental study and results, followed by a discussion and analysis in Section V. Section VI concludes this research work.

II. Related Work

A. Urban Traffic Anomaly Detection

Nguyen *et al.* [12] proposed two-step-based solutions for vehicle anomaly detection. The process starts by detecting vehicles using multiple adaptive vehicle algorithms. The detected vehicles are trained in the CNN to identify anomaly events. Bai *et al.* [13] developed a three-step-based algorithm for traffic anomaly detection systems. The traffic flow is first analyzed to determine both the road segmentation and the stationary regions. The perspective map is then generated from the data derived in the first step. The spatial-temporal information matrix is finally built to identify all anomalies. Zhu *et al.* [14] developed a CNN in which the database of the images is generated from the traffic data observations while each image represents a particular state of the traffic situation in the city. The CNN is adopted to identify anomalies and every image of the traffic flow is classified into two categories, normal case vs. abnormal case. Huang *et al.* [15] studied traffic causality in a large urban network. The visible outlier features are considered as potential indicators representing abnormal behaviors of the traffic. This is realized by injecting the spatiotemporal anomalies into the deep autoencoder learning model. The proposed solution can detect contours around the zones causing anomalies in the network, which helps the city planners to accurately get an understanding of such areas. Gu *et al.* [16] proposed an intelligent model for passenger flow anomalies. Hybrid k-means and hierarchical clustering algorithms are first performed to discover the passenger flow represented by time-series data. The anomaly detection indexes are generated to represent the different types of passenger flow outliers using a threshold algorithm. The different detected anomalies are reported as alarms to the city planners.

B. Maritime Traffic Anomaly Detection

Some very recent studies considered the problem of anomaly detection in the context of maritime traffic data. Kim *et al.* [17] combined the anomaly detection with the Shapley additive explanations to identify and explain the outliers from maritime data. In this approach, the attribution of the features of each observation from maritime data is calculated and the segmentation is then performed for identifying clusters of maritime data, where each cluster is evaluated according to the contribution of the observations on such cluster. Han *et al.* [18] used the long-short term memory with the variational autoencoder to identify anomalies from maritime data. The approach is semi-supervised as the training data is not fully labelled. This reflects much better the current scenarios in which the normal behaviors are captured by the sensors. Abreu *et al.* [19] developed an approach based on visual analytics to capture the different local anomalies from maritime observations. Trip outlier scoring is involved to evaluate the maritime trajectories and asset to them an outlier score. Monteiro *et al.* [20] suggested a solution to evaluate maritime operators in low computation runtime. It involves the normalized electroencephalogram energy information for identifying anomalies in such operators.

C. Artificial Neural Network for Intelligent Transportation

Many artificial neural network-based works have been developed for solving intelligent transportation problems. Chan *et al.* [21] used the neural network to estimate traffic congestion. The missing data issue is solved using the weighted averages of the historical data. It also developed a traffic simulation system, which is benchmarked using the Google Maps rerouting system. Yang *et al.* [22] analyzed artificial neural network solutions in pavement design, construction, inspection, and road maintenance. These models are based on three main architectures: The multi-layer perceptron neural network, the convolutional neural network, and the recurrent neural network. The study revealed that these models are facing huge challenges in terms of data collection, parameter optimization, and the missing ground truth. Qiu *et al.* [23] proposed deep learning for target detection. It explored the fused edge features that will be injected into the convolutional neural network for vehicle detection in the real traffic scene. Chen *et al.* [24] solved the security issue for intelligent traffic transportation. It explores the fault diagnosis for railway transportation by developing an improved RetinaNet model with the spatial attention mechanism. Both the local and global features are utilized in the learning process.

From this short literature review, we conclude that solutions to urban and maritime anomaly detection can be divided into three categories. The first category groups statistical approaches, in which normal behaviors share a statistical process while the remaining observations are considered as anomalies. The second category consists of similarity-based approaches. These approaches are based on the distance among the different observations. The normal observations are located in dense regions, while the abnormal ones are located in isolated regions. The statistical approaches are very sensitive to anomalies as it is not straightforward to capture the distribution of the normal observations and calculate the observations that do fit them. This problem was solved by the similarity-based solutions that developed non-parametric strategies. However, they are very sensitive to the distance used for computing neighbourhoods. The third category is deep learning-based approaches that use different deep architectures such as recurrent neural network (RNN), convolutional neural network (CNN), and autoencoder models to solve the problems of the other categories. They aim to train data and use a binary classifier to separate the outliers from the normal behaviours. Nevertheless, the entire training data is considered in the learning phase. This results in a weak detection rate even when

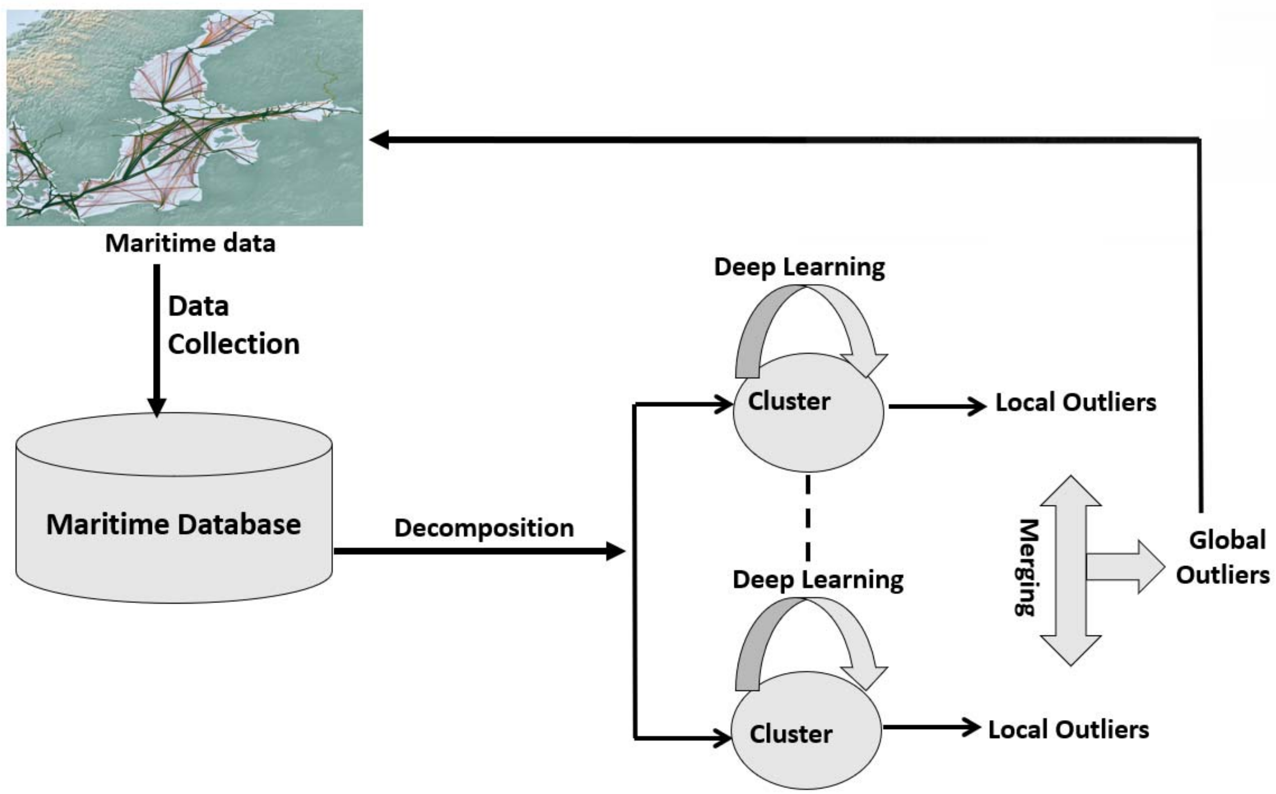

Fig. 1. Illustration of the DCNN-TFO Framework. The maritime image is retrieved from https://github.com/hakola/marine-traffic-modelling.

employing intensive computing technologies. Moreover, these deep learning architectures are composed of many layers and then require a high number of hyper-parameters to be correctly tuned. Randomly setting these hyper-parameters without a comprehensive study might also degrade the accuracy. Inspired by the achievement of the cluster-based algorithms [9], [25], [26] in solving complex problems, we develop a hybrid fusion algorithm that combines decomposition and CNN to efficiently explore the maritime data and identify relevant outliers in real-time processing.

III. Intelligent Deep Fusion Network Anomaly Detection

A unique deep learning method for finding abnormalities in marine data is discussed in this section. As shown in Fig. 1, the proposed solution is based on a CNN. It considers the maritime data represented by images, the data is collected from drones. This input is first plugged into a decomposition model that produces another layer of input to the CNN, which consists of a set of clusters. As a result, different models are generated, each of which is assigned to one cluster of maritime data.

A. Decomposition

The decomposition step aims at decomposing the set of maritime data into similar clusters. The goal is to determine a set of clusters to which we can assign maritime observations, using the minimization of the distances between the observations of the cluster and its centroid as the decomposition criterion. We need to optimize the following function:

$$\mathcal{DC} = argmin \sum_{i=1}^{k} \sum_{M_j \in C_i} D(M_j, g_i), \tag{1}$$

where M_j is the maritime data, C_i is the i^{th} cluster, and g_i is the centroid of C_i. For this purpose, we use the k-means heuristic. It starts by randomly initializing the centroids of the clusters. The distance between the centroids and each maritime data is then determined, and a maritime datum is assigned to the cluster with a low distance value. After assigning all the maritime data, the centroid of each cluster is updated. This process is repeated until either convergence or reaching the maximum number of iterations. The convergence is reached if and only if the value $\sum_{i=1}^{k} \sum_{M_j \in C_i} D(M_j, g_i)$ is less than a given threshold chosen by the user.

B. Convolutional Neural Network (CNN)

The proposed approach is inspired by the Faster RCNN principle [27], which is a state-of-the-art object detection solution. In our context, the objects to be identified are anomalous from maritime images. The set of region candidates determined is first performed. The goal is to calculate the regions of interest, the potential areas represent the bounding boxes that include the object. The selective search generates a high number of bounding boxes per image, which makes it difficult to use this process in a real scenario. In our solution, we employ an efficient strategy to retrieve the bounding boxes from maritime data that consists of exploring the CNN to learn the bounding boxes based on the ground truth of the training images. After determining the bounding boxes, a regression technique is established to refine the results and obtain bounding boxes with high precision. The process starts by training the CNN model using the transfer learning process on each cluster of maritime data generated in the previous step. The result of this step is the set of generated bounding boxes. As a result of our rigorous negative generation, the models we train benefit greatly. A feature concatenation is used in conjunction with multi-scale training to improve the performance of the trained model. A detailed explanation of these steps is given below:

1) **Feature concatenation:** In the existing detection algorithms, the final feature map layer pools the regions of interest to create the region's features. This approach is deficient because it omits key elements, reducing its precision. Feature maps from several convolution layers with different level characteristics are combined to overcome this restriction. The final pooling features for detection are generated by concatenating and re-scaling L2 normalized pooling results from various feature maps.
2) **Hard negative mining:** The goal of this technique is to find models that forecast incorrect or hard negatives of the regions. Models utilizing reinforcement learning to improve their performance have negative values injected into them. These regions are deemed hard negatives if their intersection with ground truth is less than 40% in the second iteration of the training process, where they are harvested as hard negatives.
3) **Multi-scale training:** The existing object detection algorithms use a fixed scale when generating the bounding boxes. Objects to be identified in real-world applications, such as data on urban transportation, are multi-scale. Bounding boxes are generated using a variety of scales. The scales of bounding boxes used in this study are tiny, small, medium, large, and big. Because of this, five separate sets of bounding boxes are produced, each with the same size. For each set of bounding boxes, the region proposal decision process is initiated. After this phase, the produced bounding boxes are combined with the CNN for the classification and regression processes.

Different optimization is then carried out to tune the hyper-parameters of the trained model using an evolutionary algorithm. The set of all parameters of the developed models is considered as the solution space. The crossover, the mutation, and the selection operators are then explored to find the optimal values of such parameters.

C. Fusion Model

This phase aims to illustrate whether the local outlier found on each cluster can be generalized to all clusters and considered as a global outlier. It combines the model results acquired in the previous stage. Based on ensemble learning [28], a voting strategy is used to find the final result of the proposed framework. We assume k different models $\{m_1, m_2, \ldots, m_k\}$, and that each model m_i provides an output O_i indicating whether the corresponding input is an outlier or not. We assume that O_i is set to 1 if the model, M_i, considers the current input as an outlier and 0, otherwise. We first sum all outputs of the k models as:

$$O = \sum_{i=1}^{k} O_i \tag{2}$$

If O is less than $\frac{k}{2}$, then the current input is considered as normal maritime data, and outlier otherwise. The fusion model used is an approximate-based model where we cannot guarantee the correctness of the final output. We aim to converge to the optimum solution by reducing the loss. This will be validated in the experimental phase.

Algorithm 1 DCNN-TFO Algorithm

1: **Input**:
   $M = \{M_1, M_2, \ldots, M_n\}$: the set of n maritime data.
2: **Output**:
   $model$: the model generated in the training phase.
3: $M \leftarrow CollectionFromDrones(Drones)$;
4: $G \leftarrow Decomposition(M)$;
5: $models \leftarrow \emptyset$;
6: **for** $G_i \in G$ **do**
7:   $model_i \leftarrow ImprovedFastRCNN(G_i)$;
8:   $model_i \leftarrow Evolution(model_i)$;
9:   $models \leftarrow models \cup \{model_i\}$;
10: **end for**
11: $model \leftarrow fusion(models)$;
12: **return** $model$.

D. Algorithm

Algorithm 1 presents the pseudo-code of the DCNN-TFO. The input data is the set of maritime data used for the training. The data contains the set of images collected from drones. The ground truth is also provided, which is represented by a label indicating if the current maritime image is normal or outlier. The output will be the trained model by the DCNN-TFO. The process starts by collecting the maritime images from the drones (line 3). These images are then decomposed into similar clusters as illustrated in line 4. The improved faster RCNN algorithm developed in Section III.B is trained on each cluster of maritime images. The concatenation of all models is determined as shown from line 5 to line 10. In this step, the evolutionary algorithm is performed for optimizing the parameter of each model using the evolution function as described in line 8. The fusion is finally executed to merge the final outputs of all models of all clusters (line 11). The trained model is returned as revealed in line 12.

IV. Performance Evaluation

Intensive experiments have been carried out for the validation of the proposed framework. Two kinds of data have been used: 1) Experiments on urban traffic data, where two datasets were used Odense,[1] and Beijing,[2] 2) experiments on well-known maritime datasets, Aerial Maritime,[3] and Singapore Maritime.[4] The evaluation is performed using different measures: True Positive Rate (TPR), True Negative Rate (TNR), and Area Under Curve (AUC), which are the frequently used metrics for evaluating outlier identification techniques.

A. Urban Traffic Data Experiments

Several experiments have been carried out using Odense and Beijing data by varying the percentage of the urban traffic data used from 20% to 100% and using different metrics mentioned above (TPR, TNR, and AUC). We used two baseline algorithms, the first one is based on CNN [29] which is a deep learning network for identifying outliers, and the second one is based on SVM (Support Vector Machine) [30] which is a traditional machine learning solution in deriving the outliers. Fig. 2 (top) presents the true positive rate by varying the percentage of the data used as input from 20% to 100% on both Odense and Beijing data. The results reveal the clear superiority of the proposed DCNN-TFO compared to CNN and SVM. Indeed, the TPR of the DCNN-TFO does not go below 0.75 and exceed 0.85, where CNN does not exceed 0.82, and SVM does not exceed 0.70. Fig. 2 (middle) presents the true negative rate by varying the percentage of the data used as input from 20% to 100% on both Odense and Beijing data. The results reveal again the clear superiority of the proposed DCNN-TFO compared to CNN, and SVM. Indeed, the TNR of the DCNN-TFO does not go below 0.80 and exceed 0.90, where CNN does not exceed 0.80, and SVM does not exceed 0.75. In terms of AUC, the results are shown in Fig. 2 (bottom), the results validate the obtained ones in the previous experiments, where the superiority of the DCNN-TFO is validated on both data (Odense, and Beijing). These promising results are reached thanks to the efficient decomposition strategy which allows splitting the whole into homogeneous clusters. This allows to better train the different models of the derived clusters.

B. Experiments on Maritime Data

The next experiment is to show the performance of the proposed solution on maritime data. We varied the percentage of the maritime data used from 20% to 100%, and we used different metrics mentioned above (TPR, TNR, and AUC). We also used the same baseline algorithms, CNN, and SVM. Fig. 3 (Top) presents the true positive rate by varying the percentage of the data used as input from 20% to 100% on both Aerial and Singapore data. The results reveal the clear superiority of the proposed DCNN-TFO compared to CNN and SVM. Indeed, the TPR of the DCNN-TFO does not go below 0.75 and exceed 0.80, where CNN does not exceed 0.74, and SVM does not exceed 0.71. Fig. 3 (Middle) presents the true negative rate by varying the percentage of the data used as input from 20% to 100% on both Aerial and Maritime data. The results reveal again the clear superiority of the proposed DCNN-TFO compared to CNN, and SVM. Indeed, the TNR of the DCNN-TFO does not go below 0.80 and exceed 0.90, where CNN does not exceed 0.77, and SVM does not exceed 0.75. In terms of AUC, the results are shown in Fig. 3 (Bottom), the results validate the obtained ones in the previous experiments, where the superiority of the DCNN-TFO is validated on both data (Aerial, and Singapore). These promising results confirm the previous ones obtained on urban traffic flow data. Indeed, the decomposition strategy used efficiently split the search space into smaller but homogeneous regions, easy to be trained by the deep learning models. The fusion model suggested in this research work also allows for accurately merging the local results.

V. Discussion and Future Perspectives

A. Main Findings

The results show that the proposed framework (DCNN-TFO) can deal with big urban traffic data, e.g., Beijing, and Singapore data, and considerably reduce the runtime compared to existing approaches to quickly detect anomalies. It is not limited to deriving outliers but enables studying the different correlations between these observations and retrieving disjoint groups [31]. DCNN-TFO is an intelligent framework that combines data mining and deep learning throughout different phases, such as decomposition, and learning processes. Additionally, this study discovered that deep learning models benefit from preparing data by using decomposition to speed up the identification process. Finally, it is worth noting that the framework provided in this study is general and may be used to any form of network data, in contrast to previous methods that are limited to a certain type of urban or marine data. The datasets illustrated in this paper are just examples of applications, but other data such as trajectories [32], time series [33] and other [34], [35] may be dealt with by our framework.

B. Visions for Future Directions

More efforts are needed to minimize the number of shared urban traffic data among clusters in the decomposition. Integrating other decomposition techniques such as multi-objective clustering [36] with the DCNN-TFO framework might be a promising approach. Automatically fixing the number of clusters is another perspective that yields from this study. Performing several runs to find the best values of the number of clusters is ineffective. As an alternative, you might construct a knowledge base including the appropriate number of clusters for each training set of urban traffic data and then analyze the relationships between these meta-features (number of flow values, number of trajectories, and so on) and the optimal values of the number of clusters. Thus, the ideal number of clusters in the new urban traffic data may be predicted automatically. To further improve the performance of DCNN-TFO for large-scale applications, we want to use metaheuristics such as genetic algorithms [37]. The challenge will be to efficiently create an independent job for each cluster

[1] https://www.odense.dk/
[2] https://www.beijingcitylab.com/
[3] https://www.kaggle.com/ammarnassanalhajali/aerial-maritime
[4] https://www.kaggle.com/adnanenasser/singapore-maritime

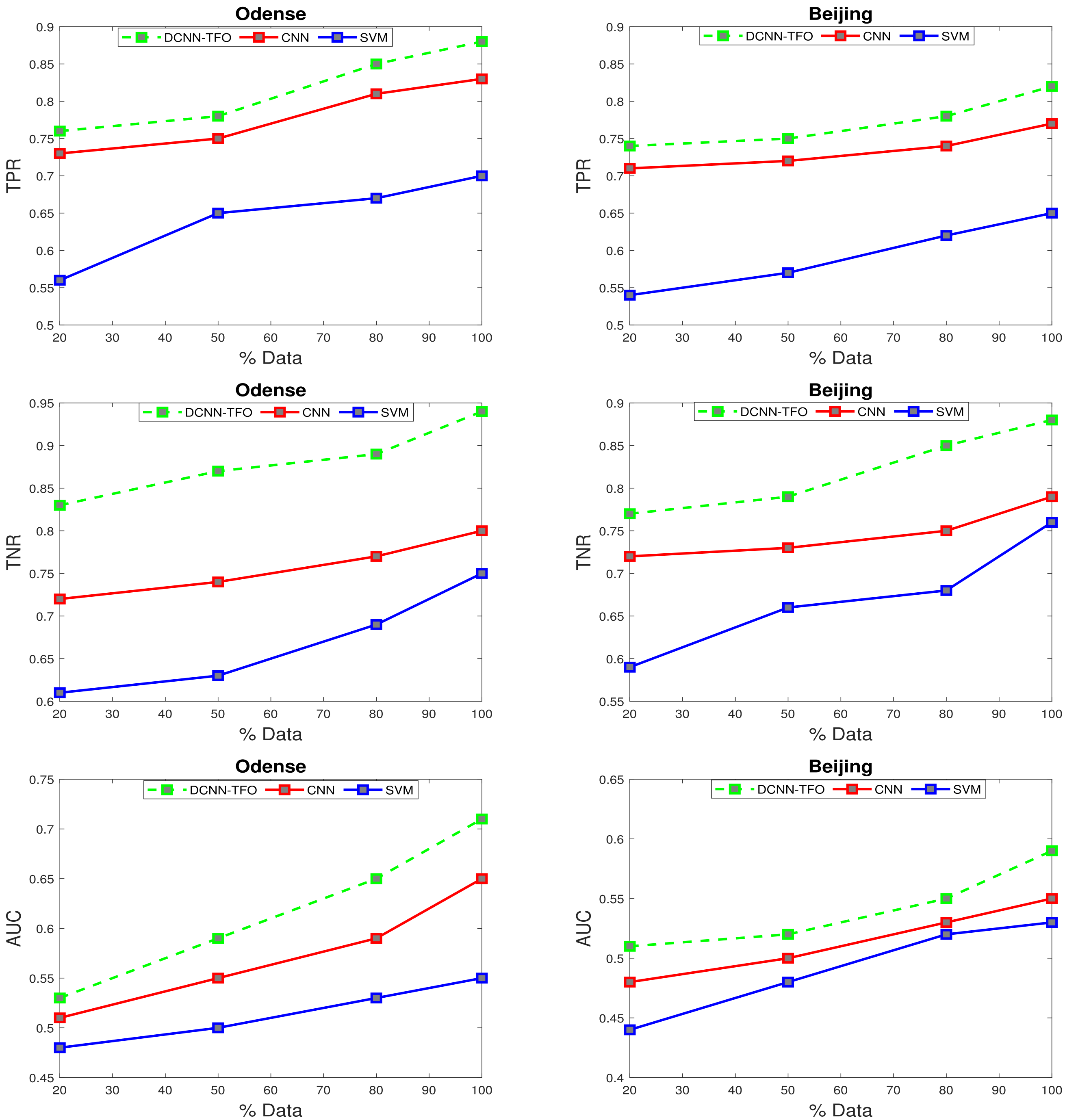

Fig. 2. Experiments on urban traffic data.

of urban traffic data while observing the HPC requirements, i.e., synchronization, communication, memory management, and load balancing. We are particularly considering strategies for load balancing. One method to solve this is to develop decomposition algorithms that enable the identification of equitable clusters based on the amount of urban traffic data included in each cluster. Another aim is to create novel techniques for cluster repair to identify clusters that contain about the same amount of urban traffic data.

Motivated by the promising results of the case studies of this work, We want to develop DCNN-TFO to address domain-specific difficult challenges that need the management of large amounts of data, such as business intelligence applications or mining financial data mining. Runtime performance is particularly essential in automated trading systems, which frequently profit from the volatility of share prices or currency rates in relatively short periods. Outlier detection systems capable of detecting abnormal patterns in these instances will create new chances for more intelligent trading. Another possible use is sensor data processing, most especially for real-time applications connected to Internet of Things (IoT) systems including energy management in smart buildings and smart

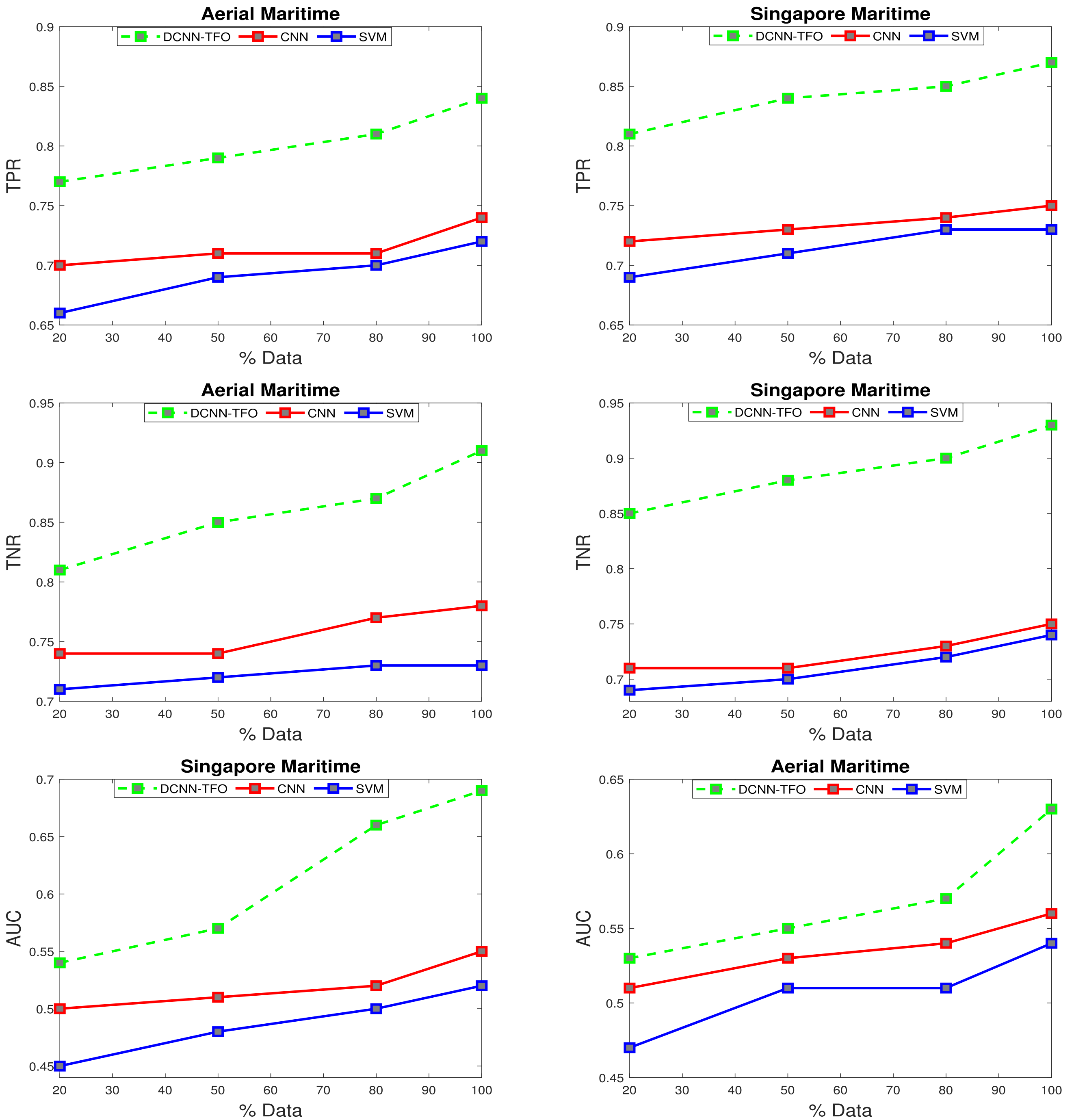

Fig. 3. Experiments on maritime data.

grids [38]–[41], smart city and related services [42]–[44], and data fusion [45] where outlier detection must be conducted with very low latency.

VI. Conclusion

In this paper, we explored decomposition and deep learning to accurately detect abnormal behavior from marine data. The data is first divided into clusters using an approach that groups similar data in the same cluster and inserts them into a convolutional neural network (CNN). This makes the training process of the CNN simple and is more oriented towards homogeneous behaviors. As a result of this combination, several models are trained, each for the data of the corresponding cluster. The fusion model is developed to combine the results of the trained models. Intensive experiments were conducted to obtain a better validation process for the proposed framework. The results on maritime data show the effectiveness of the proposed framework compared to the state-of-the-art methods for outlier detection using different metrics.

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