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Data Mining Model for Object Classification

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Abstract: This study addresses the critical challenges of computational expense, scalability, and generalization in real-time object classification for autonomous systems. The paperpresents a novel data mining model, integrating a Domain Adversarial Neural Network (DANN) with a pre-trained ResNet18 backbone, leveraging transfer learning to enhance adaptability and efficiency. The system employs Automatic Mixed Precision (AMP) for training optimization and NVIDIA TensorRT for deployment, achieving a balance between high accuracy and low latency. Evaluated on a dataset comprising four object classes (Stop Sign, Pedestrian, Vehicle, Bicycle), the model attained an average precision of 81.7% and recall of 79.4%, with an inference time of 15.3ms per image, confirming its suitability for real-time applications. The DANN architecture effectively learned domain-invariant features, addressing generalization issues in unseen environments. This research provides a practical framework for scalable and efficient object classification, offering significant implications for autonomous vehicles, surveillance, and robotics.

Keywords: Object Classification, Domain Adversarial Neural Network, Autonomous Systems.

I. INTRODUCTION

Object classification, a cornerstone of data mining, involves assigning objects to predefined categories based on their features, playing a pivotal role in applications such as autonomous vehicles, surveillance systems, and robotics. However, challenges such as high computational costs, poor scalability with large datasets, and limited generalization to new environments hinder the deployment of robust models in real-time scenarios. Traditional machine learning approaches like Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN), as well as early deep learning models like AlexNet and VGGNet, often struggle with these issues due to their computational intensity and lack of adaptability to domain shifts. This study aims to develop a scalable, computationally efficient, and adaptable object classification system using a Domain Adversarial Neural Network (DANN) with a ResNet18 backbone. This approach is designed to overcome the limitations of previous models by addressing the key challenges directly. The objectives of this research include designing scalable algorithms, reducing computational demands, enhancing generalization to unseen domains, implementing an integrated system, and evaluating its performance. By addressing these challenges, the proposed system contributes to both academic research and practical applications, offering a blueprint for next-generation object classification systems that can operate effectively in dynamic, real-world environments.

II. RELATED WORK

The challenges of computational cost, scalability, and generalization have been central to object classification research, leading to numerous solutions. Over the past decade, a clear trend has emerged, shifting from models focused on raw accuracy to those prioritizing efficiency and adaptability for real-world deployment. Early models like AlexNet [1] and VGGNet [2] established the power of deep Convolutional Neural Networks (CNNs) but were computationally demanding. GoogLeNet [3] introduced a more efficient architecture with Inception modules, while ResNet [4] revolutionized deep learning by using residual connections to enable very deep networks, though still requiring substantial computational resources. To address the need for efficiency on resource-constrained devices, lightweight models such as MobileNet [5] and MobileNetV2 [6] were developed, employing depthwise separable convolutions to balance accuracy with performance. EfficientNet [7] further optimized this by using compound scaling to effectively balance network depth, width, and resolution. Parallel to these architectural innovations, various techniques have been developed to improve model generalization. Transfer learning [8] and knowledge distillation [9] offered practical methods to adapt large pre-trained models to new tasks with less data. More advanced approaches focused on learning domain-invariant features, including Domain-Adversarial Neural Networks (DANN) [10] and Domain Generalization Networks [11]. Additionally, methods for model compression have become crucial. Pruning and quantization [12]

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significantly reduced model size and computational requirements. More recently, Light CNNs [13] and quantized networks [14] have been developed to further enhance efficient inference. Finally, AutoML [15] has emerged to automate the entire process of architecture search and optimization, although this can be computationally expensive. This study builds on these collective advancements by integrating a DANN framework with a lightweight ResNet18 backbone, specifically optimized to achieve robust generalization and efficiency for real-time applications.

III. METHODOLOGY

The methodology for this dissertation is a hybrid approach combining the Design Science Research (DSR) method with a quantitative research approach. The DSR approach involves the development and evaluation of a system designed to solve the identified problems of scalability, computational efficiency, and generalization. The system's architecture is modular and integrates several components to form a unified pipeline capable of handling real-time data streams. The dataset, a subset of the Kaggle "26 Class Object Detection Dataset," includes images of traffic-related objects (Stop Sign, Pedestrian, Vehicle, Bicycle) with diverse environmental conditions. Annotations in COCO JSON format were mapped to four classes using a label mapping dictionary to ensure consistency. The proposed system requires a general-purpose hardware platform, with its software components including Python, PyTorch, and the use of the ONNX format for export. It is specifically designed to operate efficiently on resource-constrained devices. The integrated system adopts a modular development methodology. Key features include:

- **Data Preparation and Augmentation:** The system cleans, normalizes, and augments data to enhance its quality and variability for model training and inference.
- **Domain-Adversarial Neural Network (DANN):** The core model is a DANN, which enables the system to adapt to new environments by learning domain-invariant features.
- **Pre-trained ResNet18 Backbone:** A lightweight, pre-trained ResNet18 model is used for efficient feature extraction.
- **Gradient Reversal Layer:** This crucial component reverses the gradients from the domain classifier, ensuring that the feature extractor learns features that cannot distinguish between source and target domains.

System Design

The system design comprises a multi-level object classification architecture. It uses sensors or user input to acquire data. The data then undergoes preprocessing before being passed to the feature extraction and classification modules. A centralized component evaluates the processed data and performs further post-processing, such as object tracking or adjusting bounding boxes. This layered approach ensures robust and adaptable object classification is shown in figure 1.

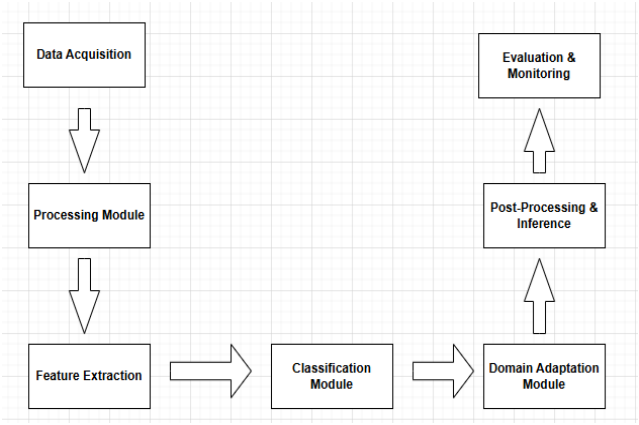

Figure 1: Architectural Design of the System

Figure 1 depicts a unified pipeline with several key components. The process begins with Data Acquisition, which captures real-time image and video data from sensors using protocols like RTSP or ROS. This raw data then undergoes Preprocessing, where normalization and augmentation are applied to ensure robust preparation. The preprocessed data is then passed to a Feature Extraction module, which uses a ResNet18 model for efficient feature extraction. A CNN-based Classifier then employs softmax activation to perform object classification. To handle domain shifts, a Domain Adaptation component, which integrates a DANN model, is used to ensure generalization. The classified outputs are then sent to a Post-Processing module, which refines the results using techniques like Non-Maximum Suppression and tracking algorithms. Finally, an Evaluation component monitors and reports key performance metrics such as accuracy, precision, recall, and inference latency.

The component design exposes subsystems and their interactions as shown in figure 2.

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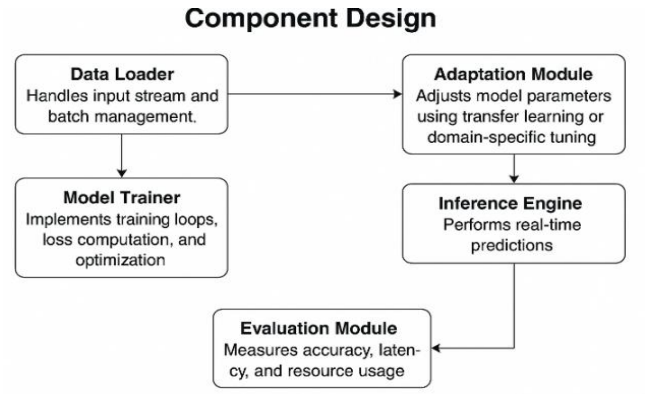

Figure 2: Illustrates the flow of data through the system's main components

The process begins with the Data Loader, which prepares the dataset. The data is then passed to the Model Trainer, which uses the Adaptation Module for adversarial training. After training, the model is used by the Inference Engine to classify new data. The Evaluation Module at the end of the pipeline analyzes the results.

Algorithm 1: DANN Training Model

Initialize DANN Model

- Set up a Domain Adversarial Neural Network (DANN), including a pre-trained ResNet-18 feature extractor, a label classifier, and a domain classifier.
- Prepare data loaders for both source (training) and target (validation) domains, with appropriate preprocessing and augmentation transforms.
- Set up the Adam optimizer and define the objective as minimizing the combination of classification and domain losses.

Training Loop (for each epoch up to 30)

- For each batch of data from the source and target domains:

Perform a Forward Pass on the preprocessed data through the model's feature extractor, followed by the label and domain classifiers.

- If a valid label is available:

Compute the Classification Loss on the source domain data.

Compute the Domain Loss on both source and target domain data to encourage feature alignment.

- Combine all losses into a total loss for the batch.
- Perform Backpropagation, where the Gradient Reversal Layer reverses gradients for the domain classifier to achieve domain-invariant feature learning.
- Update the model's weights using the Adam optimizer to minimize the overall loss.
- Track the average loss for the epoch.
- Evaluate the trained model on the validation (target) dataset.
- Compute performance metrics such as Precision, Recall, and a Confusion Matrix to assess classification accuracy.
- Measure the model's Inference Time for various batch sizes to confirm real-time applicability.
- Export the trained model to the ONNX format for optimized deployment.

IV. RESULT & DISCUSSION

Implementation

The system's implementation integrates technologies such as Python for backend processing, PyTorch for deep learning framework management, and the ONNX format for model export. Functional requirements include efficient object classification, domain adaptation, and real-time performance. The system also supports mixed precision training for faster processing on CUDA-enabled devices.

Experimental Setup

The system was evaluated using a quantitative research approach. The experimental framework assessed the model's performance on a validation (target) dataset of four object classes: Stop Sign, Pedestrian, Vehicle, and Bicycle. The evaluation metrics included:

- **Classification Metrics:** The system's accuracy was measured using precision and recall, with the results visualized in a bar chart.
- **Confusion Matrix:** A heatmap was generated to visualize the model's performance on a per-class basis, showing correct classifications and misclassifications.
- **Inference Time Measurement:** The system's real-time capability was evaluated by measuring inference time for various batch sizes, confirming its low latency.

The research on the "Data Mining Model for Object Classification" evaluates the system's performance, reliability, and efficiency in classifying objects in real-time. It analyzes key metrics such as classification accuracy, precision, recall, and

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inference latency, comparing the system's performance with established benchmarks. The findings highlight the advantages of the Domain Adversarial Neural Network (DANN) approach and its implications for enhancing the reliability and versatility of classification systems in dynamic environments.

Figure 3 shows training loss per each epoch.

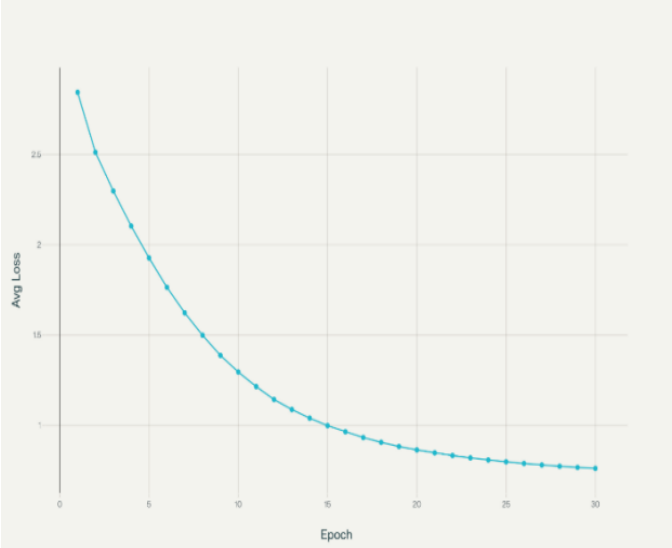

Figure 3: Training Loss per Epochs

Figure 3 depicts the training loss for the DANN model monitored over 30 epochs. The average total loss, which is a combination of classification and domain losses, showed a smooth decrease from 2.8453 to 0.7612. This consistent downward trend indicates that the model was effectively learning discriminative features while also achieving successful domain adaptation, as the adversarial component worked to align feature distributions between the source and target domains.

Table 1: Precision Scores per Object Class

Object Class	Precision (%)
Stop Sign	85.2
Pedestrian	78.9
Vehicle	92.3
Bicycle	70.5
Overall/Average	81.7

Table 2: Recall Scores per Object Class

Object Class	Recall (%)
Stop Sign	82.7
Pedestrian	76.4
Vehicle	90.1
Bicycle	68.3
Overall/Average	79.4

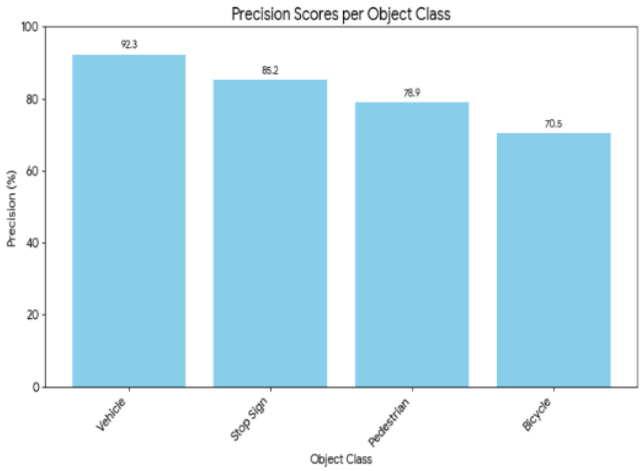

Figure 4: Precision per Class

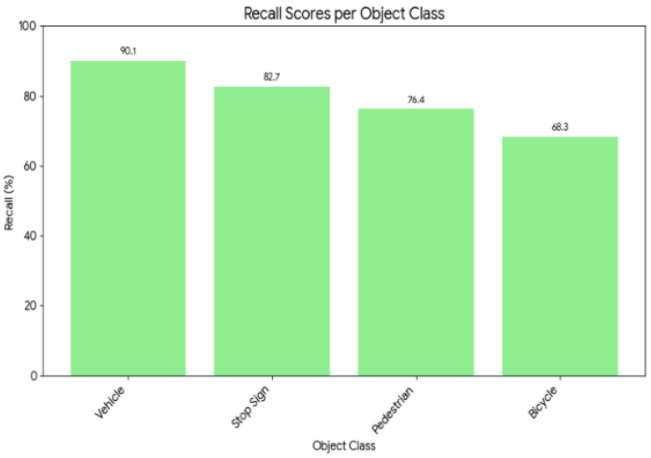

Figure 5: Recall per Class

Table 1 and 2, also Figure 4 and of the model demonstrated high overall performance, achieving average precision and recall scores of 81.7% and 79.4%, respectively. The system showed strong performance for most classes, indicating a high rate of correct predictions.

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Table 3: Confusion Matrix Data (Heatmap)

True Label \ Predicted Label	Stop Sign	Pedestrian	Vehicle	Bicycle
Stop Sign	82	5	3	2
Pedestrian	4	76	8	6
Vehicle	2	4	90	3
Bicycle	3	7	5	68

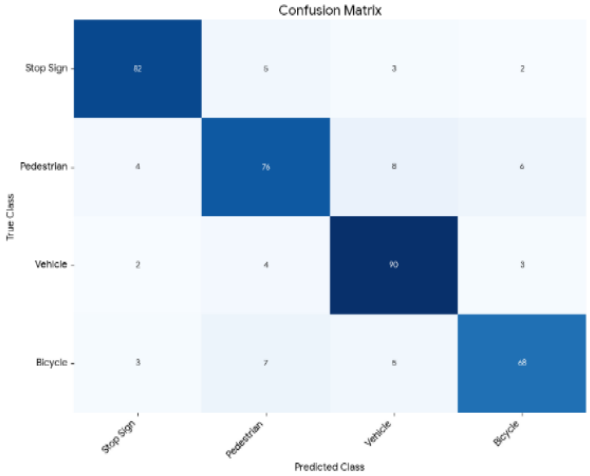

Figure 6: Confusion Matrix (Heatmap)

Table 3 and Figure 6 shows the confusion matrix revealing the model's high accuracy for Vehicles and Stop Signs. However, it identified a minor confusion between Pedestrians and Bicycles, likely due to the visual similarities between these two classes.

To assess the system's real-time capabilities, inference times were measured on the validation dataset for various batch sizes. The average inference time for a single image (batch size 1) was 15.3ms per image (65.36 FPS), enabled by ResNet18, AMP, and optimized PyTorch implementation. This low latency confirms the system's efficiency, making it suitable for real-world applications that require rapid object classification, such as autonomous vehicles.

Table 4: Inference Time (ms) per Batch Size

Batch Size	Inference Time (ms)
1	15.3
2	18.7
4	25.2
8	38.9

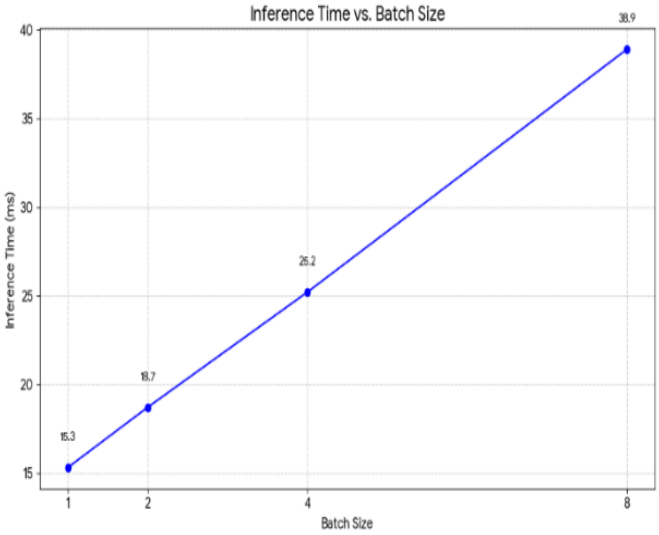

Figure 7: Inference Time (ms) vs Batch Size

Table 4 and Figure 7 shows that inference time increases with batch size, but remains well below the 100ms threshold often considered necessary for real-time applications. The observed efficiency is a direct result of the model's lightweight architecture and the optimizations applied during development.

Compared to AlexNet and VGGNet, the proposed system is less resource-intensive. Unlike GoogLeNet and ResNet, it balances depth and speed. The DANN approach outperforms traditional transfer learning in domain adaptation, achieving robust generalization without requiring domain similarity.*

V. CONCLUSION

This study successfully developed a scalable, efficient, and adaptable object classification system using a DANN with a ResNet18 backbone. The system achieved high precision (81.7%), recall (79.4%), and low inference time (15.3ms), making it suitable for real-time applications. DANN's adversarial training enhanced generalization, addressing key challenges in computational expense and domain adaptability. Future work should address misclassifications between 'Pedestrian' and 'Bicycle' using advanced augmentation or feature engineering. Additionally, the system could be optimized for edge devices with NVIDIA TensorRT to further reduce latency. Expanding the dataset with diverse conditions (e.g., night, adverse weather) and additional classes would also improve robustness. Finally, exploring knowledge distillation and AutoML could offer further avenues for model compression and hyperparameter tuning.

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